CRANFIELD UNIVERSITY

ABDULLAH ALENEZI

Framework to Assess the Maturity Level of Learning Analytics in Higher Education and Drive Learning Services Improvement

SCHOOL OF AEROSPACE, TRANSPORT AND MANUFACTURING

PhD
Academic Year: 2016 - 2020

Supervisor: Dr Christos Emmanouilidis
Associate Supervisor: Dr Ahmed Al-Ashaab

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This thesis is submitted in partial fulfilment of the requirements for the degree of PhD

LIST OF PUBLICATIONS

Alenezi, A., & Emmanouilidis, C. (2017, September). Utilising Learning Analytics in Knowledge Management Adoption for Effective Manufacturing Education. In *Advances in Manufacturing Technology XXXI*. 15th ICMR International Conference on Manufacturing Research (United Kingdom), London (534-539). ICMR. doi: 10.3233/978-1-61499-792-4-534

Alenezi, A., Emmanouilidis, C., & Al-Ashaab, A. (2018, October 21-27). *Knowledge Management to Support Learning Analytics in Higher Eduction*. IEEE 5th International Congress on Information Science and Technology (CiSt). Marrakech, Morocco. doi:10.1109/cist.2018.8596653

Alenezi, A., Emmanouilidis, C., & Al-Ashaab, A. (2018, October 30 - November 1). *Learning Analytics Framework for Higher Education based on Knowledge Management*. 17th IFIP WH 6.11 Conference on e-Business, e-Services and e-Society (I3E 2018). Kuwait City, Kuwait

ABSTRACT

This research was aimed at developing a framework that could be utilised to assess the maturity level of learning analytics (LA) in virtual learning environment (VLE) in higher education institutions (HEI). The assessment of the maturity level of LA in VLE in HEI contributes to enhancing the educational learning programmes and academic services offering to the learners. The successful implementation of LA in an HEI could help improve teaching and learning processes, thereby improving students' learning experiences (Larrabee Sønderlund et al., 2019; Sclater et al., 2016; Waheed et al., 2020). However, most HEIs often do not know where to start from in implementing programmes for using VLE and LA; thus, the contribution of this study to offer guidance for HEIs.

In order to develop the LA maturity assessment framework, a multi-phases methodological approach was adopted which involved 6 key phases (understanding the literature, a field study to gain a high-level perspective of VLE and LA, development of LA maturity model, development of a performance measurement tool, formulation of road map recommendations, and case study validation and expert judgment).

The developed LA maturity model comprises of five levels: basic (level 1), developing (level 2), functional (level 3), advanced (level 4) and optimised (level 5). In determining these LA maturity level, the performance measurement tool has to be applied. This performance measurement tool assesses an HEI's performance in four key components of LA: process, infrastructure, data and human resources and skills. The LA maturity model and performance measurement tool facilitate the road map recommendations. Based on an HEI's assessed LA maturity level, recommendations are suggested on how progress can be made in LA implementation.

The developed LA assessment framework was validated through case studies (PAAET and Cranfield University) and expert judgement that proved its validity and application to different educational contexts. The case study validation showed the differences in performance scores and maturity levels of the two HEIs with specific recommendations relevant to each context being made. Expert judgements highlighted the contribution of the framework to LA which is a relatively new area of research.

Keywords:

Learning analytics, virtual learning environment, higher education institution, multi-phases approach, maturity model, performance measurement tool, road map recommendation.

ACKNOWLEDGEMENT

To Allah, the most merciful and compassionate!

I am grateful to a lot of people that have made my PhD dream possible. Their support, prayers, encouragement and patience made this dream a reality.

Thanks to my supervisors, Dr Christos Emmanouilidis and Dr Ahmed Al-Ashaab. I am deeply indebted for their invaluable support, patience, motivation, and immense knowledge throughout the period of my research.

A special thanks also goes to my father Professor Feraih Alenezi and my mother Rafha Alenezi. Thanks for inspiring and believing in me!

To my family, thanks for your patience and enduring my absence. To my wife, Khuloud, and my children, Feraih, Lamar and Mayar for the encouragement and passion. To my brothers, Fahad, Khaled and Mohammad and my sisters, Tahani, Eman and Hajer, for motivating me to finish this journey and be an inspiration.

My gratitude also goes to my sponsors, the Public Authority for Applied Education and Training, for enabling me to pursue my dream. Thank you!

To my research participants, I wish to say many thanks for sharing your insight/views. To all others that have made an indirect contribution to this research project, I remain grateful.

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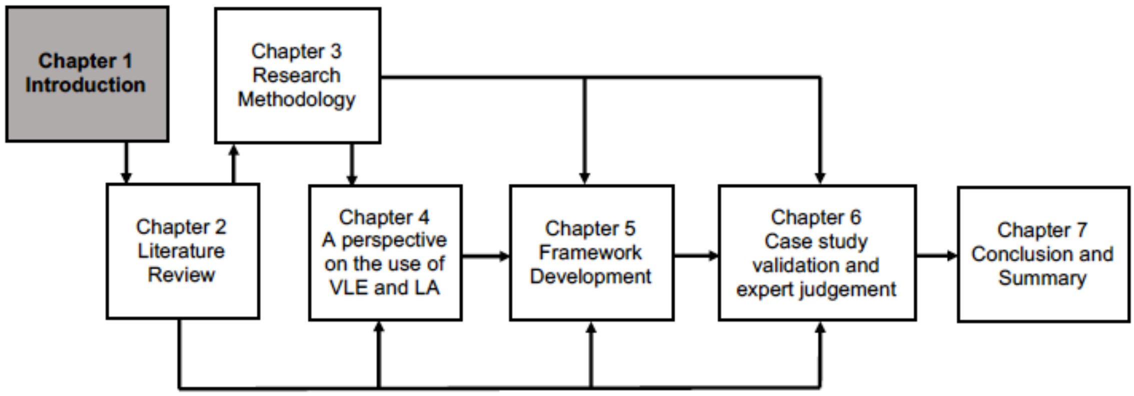
LIST OF ABBREVIATIONS

EDM	Educational Data Mining
HEI	Higher Education Institution
HeLF	Heads of eLearning Forum
ICT	Information and communications technology
KPI	Key Performance Indicator
LA	Learning Analytics
LMS	Learning Management System
MOOC	Massive Open On-Line Course
PAAET	Public Authority for Applied Education and Training
PLE	Personalised Learning Environment
PRES	Postgraduate Research Experience Survey
PTES	Postgraduate Taught Experience Survey
QAA	Quality Assurance Agency for Higher Education
SoLAR	Society for Learning Analytics Research
TeL	Technology Enhanced Learning
VLE	Virtual Learning Environment
xAPI	Experience Application Program Interface

1 INTRODUCTION



1.0 Introduction

This chapter presents an overall idea of the research. The chapter covers the research background, problem identification and motivation for undertaking this research, the aim and objectives, the research significance and an outline of the thesis. The overarching aim of the research is to develop a maturity assessment framework of the use of learning analytics (LA) in virtual learning environment (VLE) for higher education institutions (HEIs). This is to enhance the learning programmes and service offering the learners. The working definition of LA adopted in this research is that provided by the Society for Learning Analytics Research (SoLAR) that define LA as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Long and Siemens, 2011, p. 34).

1.1 Background and research motivation

Educational institutions accumulate vast amounts of data about the learners and their interactions with the learning environment (Aguilar et al., 2019; Waheed et al., 2020). The integration of digital technology into educational delivery influences both teaching and learning practices (Viberg et al., 2018) and allows access to this vast amount of data, mainly available from virtual learning environments (Ferguson, 2012; Strang, 2017). The increasing use of Virtual Learning Environments (VLEs), Learning Management Systems (LMSs) and Student Information Systems (SISs) by educational institutions has facilitated the easier access and collection of student data that could be used to improve student learning. These virtual learning environments facilitate asynchronous and synchronous interactions and communication between learners and education providers (Broadbent and Poon, 2015; Viberg et al., 2018). Virtual Learning Environments, in particular, are changing the way learning institutions deal with their teaching, learning and assessments (Boulton et al., 2018; Joint Information Systems Committee (JISC), 2016). Data created from the interactions of lecturers and learners within such learning environments comprise a rich source of information for evaluating, not only the efficacy, but also to drive improvements to the learning services. Thus, these learning environments have increasingly provided an avenue for accumulating rich data on learners from both asynchronous and synchronous interactions and communications. VLEs have provided a means to structure, manage and deliver learning activities and contents in many educational institutions around the world (Fincham et al., 2019). In this regard, Lee (2017) states that VLE has "succeeded in becoming an integral part of higher education, and now it needs to turn its focus, from providing access to university education, to increasing its *quality*". This is essentially the challenge. Through the use of VLE in learning services delivery, large datasets are accumulated about learners, their learning and the learning environment that could be utilised to better understand and support student learning (Larrabee Sønderlund et al., 2019; Schumacher and Ifenthaler, 2018; Sclater et al., 2016). In fact, every time students/learners interact with their university via the VLE, they leave behind a digital footprint (Aguilar et al., 2019; Higher Education Commission, 2016; Waheed et al., 2020). The Higher Education Commission (2016, p. 2) put this into perspective with respect to higher education institutions (HEIs) in stating that:

> In higher education, students are leaving a data footprint behind in the course of their study, which tells us about their learning and experiences at

university. Universities can use this data to understand how students learn and optimise the student experience at university.

Learning analytics (LA) provides an opportunity to exploit this rich data that is accumulated by educational institutions. LA is basically the usage of evidence and generated data from the learning environment in order to ehnance students' learning. It's a process of using the increased availability of datasets, around students' activity, students' progress, the learning context and other digital footprints lefts by students in the learning environment in order to improve learning and teaching (Alexander et al., 2019; Larrabee Sønderlund et al., 2019; Sclater et al., 2016; Waheed et al., 2020). The improvement to learning and teaching results from the analysis, explanation, prediction and action taken based on the student data collected. Thus, LA could be utilised to help an educational institution learn from its data and make informed decisions about various aspects of its learning services so as to enhance student learning and the overall students' experiences (Eberhard, 2020; Sclater, 2017). The effective utilisation of LA in VLEs, in this respect, forms a key factor to the realisation of the improvements to the learning services. The desired improvements are the basis for justifying embarking on an LA implementation project. When implemented successfully, LA could make significant contributions as (i) a tool for quality assurance and quality improvement; (ii) a tool for boosting retention rates; (iii) tool for assessing and acting upon differential outcomes among the student population; and (iv) an enabler for the development and introduction of adaptive learning (Sclater et al., 2016, p. 5).

Despite these potential benefits to the teaching and learning process, LA is still generally underutilised in HEIs (Larrabee Sønderlund et al., 2019; Viberg et al., 2018). This underutilisation of LA (including the lack of implementation) requires as a first step, the presence of an effective and efficient VLE to set the necessary conditions for the full functionality of LA (Leitner et al., 2017). In the United Kingdom (UK), for instance, LA is currently in its early development stage with most HEIs having not yet implemented a full LA project; instead, employing different platforms, methods and other metrics (Ferguson and Clow, 2017;

Shacklock, 2016). In other cases, some HEIs prioritize LA at the departmental or sectional level instead of taking it as an organisational initiative (Arroway et al., 2016). Putting this into context, Newland et al. (2015) reported that almost half of the UK's HEIs had not deployed any LA at all, with only one educational institution reported to have fully implemented a supported LA within the university. Further, for those HEIs working with or towards LA systems, there was often no consistent approach adopted within the institution itself (Higher Education Commission, 2016). The Higher Education Commission (2016, p. 13) acknowledged this underutilisation of LA in stating that "the HE sector currently possesses a rich and vast amount of data, yet is not making the most effective use of this valuable resource. The sector should seize the opportunities that data and analytics presents immediately".

A significant improvement was observed in the number of HEIs in the UK working towards implementation or having partially implemented LA from 2015 to 2017. In particular, the HEIs that were working towards implementation of LA had nearly doubled from 34% in 2015 to 66% in 2017 whilst those that had partially implemented LA increased by 5% from 17% to 23% in 2017 (Newland and Trueman, 2017). As such, the UK is beginning to wake up to the possibilities that LA provides (Higher Education Commission, 2016) based on this progression. One of the questions that could be asked is what steps can HEIs take when embarking in planning for implementing LA with VLE? Or if implemented already, what steps to progress LA with VLE implementation?

Importantly, one of the main considerations for HEIs is whether the potential benefits from a LA project implementation can actually be realised. This means overcoming major challenges that exist in embedding the use of LA into institutional practices such as "data-quality concerns, system-integration difficulties, lack of support of key leadership, and a possible faculty culture of resistance" (Arroway et al., 2016, p. 5). At this stage, the impact of LA in terms of improvement to students' learning and the overall students' experiences (Eberhard, 2020; Sclater, 2017) becomes more visible. The information about learners and the learning environment would have been accessed, elicited and analysed for “modelling, prediction, and optimisation of learning processes” (Mah, 2016, p. 35) at this level. With all the above background, this research is motivated by the need to develop a maturity assessment framework that could be utilised to evaluate the level of LA implementation in VLE. In addition, there is a need for a performance measurement tools to assess the level of education institute performance against the maturity level of using learning analytics in virtual learning environment. Furthermore, the research is motivated to provide a recommendation to education institute in order to move forward in their maturity level of using LA in VLE.

1.2 Aim and Objectives

This research aims to develop a framework that can be utilised to assess the maturity level of LA in VLE in HEIs. This is to enhance the educational learning programmes and the academic services offering to the learners. The framework includes measurement of the performance of an HEI as well as recommendations on steps to take to advance their maturity level.

In order to achieve this aim, the following research objectives will be addressed:

1. To gain an understanding of the use of LA in VLEs in order to capture the good practices of learning services in HEIs.
2. To conduct a field study in order to obtain stakeholder perspectives on the use of LA to improve learning services in HEIs.
3. To develop a framework of maturity level on the use of LA in VLEs to support learning services in HEIs.
4. To develop road map recommendations on the use of the LA in VLEs to support learning services in HEIs.
5. To validate the developed framework through case studies, and also evaluate it through expert judgment.

1.3 Research questions

The research questions of this study have been developed in order to address the research objectives above. The research questions that will be answered are:

1. What are the good practices in the use of LA in VLEs to support learning services in HEIs?
2. What are the levels of maturity in the use of LA in VLEs to support learning services in HEIs?
3. What performance measurement technique could be used to assess the maturity level of LA in the VLEs?
4. What recommended methods can be used to ensure the validity of the developed maturity assessment framework?

An outline of the thesis is given next.

1.4 Outline of the thesis

This chapter was aimed at introducing the research project. It outlined the research background and identified the research problem motivating the study. The research aim and objectives were then specified. The research questions arising from the research objectives were also elaborated. An overview of the methodological approach adopted to address the research objectives was also discussed. The contributions of the study were then highlighted.

The rest of the thesis is organised as follows. Chapter 2 gives a review of the literature on LA. This discusses in detail the multi-disciplinary nature of LA which has affected its definition followed by an overview of LA implementation in HEIs. The challenges that exist in LA implementation and the key forces/drivers are also elaborated. Some good practice cases are then reviewed before delving into a discussion of some existing maturity frameworks on LA. This review is particularly important in order to highlight the contribution of this research project to the extant LA literature through identifying existing gaps.

Chapter 3 outlines the methodological approach that underpins this study. The chapter highlights philosophical and theoretical standpoints in order to identify and position this study as a multi-theoretical study. The multi-phases methodological approach adopted is then discussed in detail outlining the six different methodological steps taken. The methodology chapter is followed by Chapter 4 that presents the findings from the field study. These findings are discussed with reference to the research methods as qualitative and quantitative. This chapter helped to obtain a high-level perspective regarding the usage of LA; giving more context for the development of the maturity level assessment framework discussed in Chapter 5.

Chapter 5 is divided into three parts. The first part details the developed maturity level model outlining the identified 5 maturity levels. The maturity levels are then related to the main stakeholder interaction processes, and to the learning services. This helps to give a more holistic presentation of the maturity level assessment framework. The second part of the chapter details the performance measurement tool developed to facilitate the application of the maturity level model. This performance measurement tool covers aspects of data, processes, infrastructure and human resources. As the maturity level assessment framework is developed with a progressive perspective, the third part of chapter 5 outlines a road map recommendation on how HEIs could make progression from lower levels in the maturity level model to more advanced stages that ensures benefits from LA to be more likely realisable.

Chapter 6 is focussed on validating the developed maturity level assessment framework. In this respect, the chapter presents case study-based evidence on the application of the developed maturity level assessment framework to different HE institutional contexts. This is followed by analysis of evaluations obtained from expert judgments on the usability of the framework.

Chapter 7 summarises the research project with respect to the research questions. The key aspects of the maturity level model, performance measurement tool and road map recommendations are discussed. The chapter then highlights the key contributions of the research to the LA research field and then makes suggestions for future research after acknowledgement of some research limitations. **Figure 1-1** gives a diagrammatic presentation of the thesis.

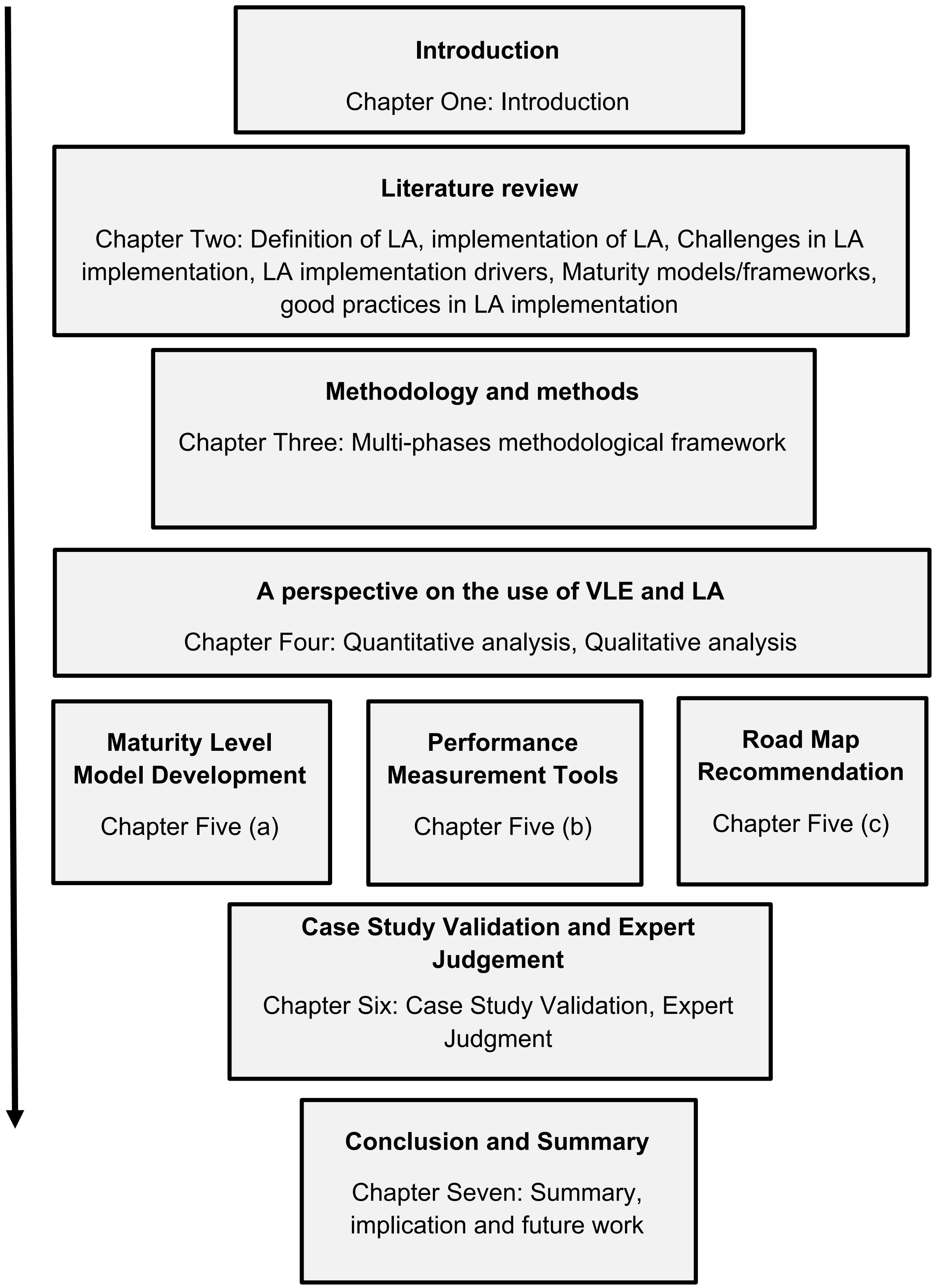
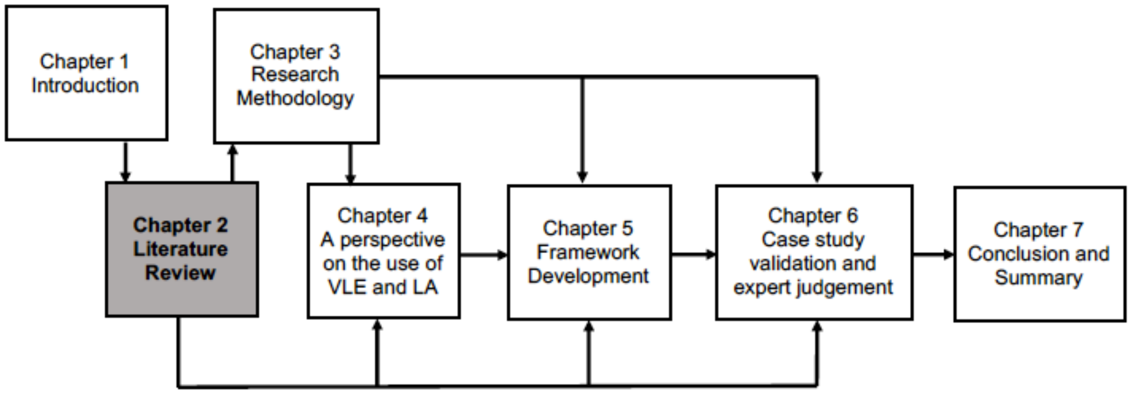


Figure 1-1: Diagrammatic presentation of the thesis.

2 LITERATURE REVIEW

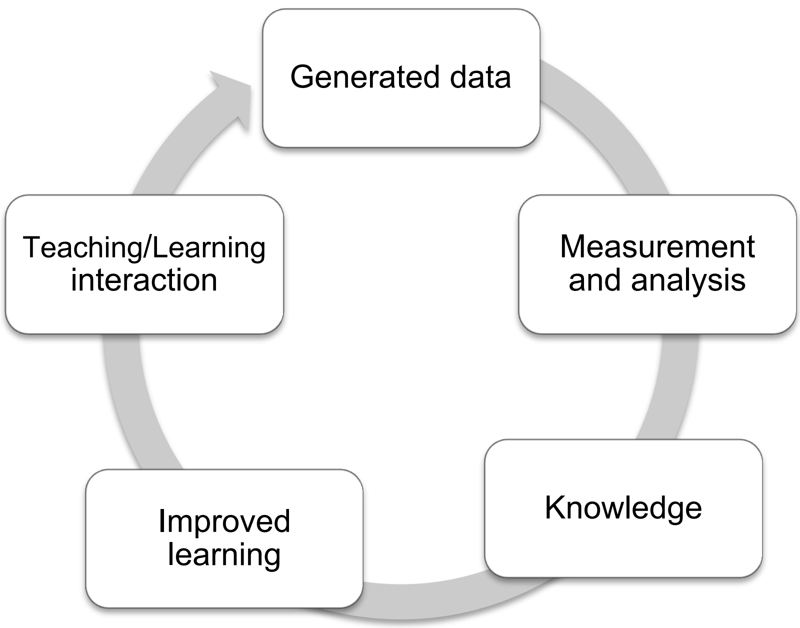


2.0 Introduction

This chapter reviews the literature on learning analytics (LA). The chapter starts with the definitions of learning analytics and learning services. This is important in order to build context as LA implementation is aimed at improving learning services; enhancing students' learning experiences and success. As LA is utilised in online learning environment, a discussion of these online learning environments with a focus on virtual learning environment (VLE) is conducted. This is followed by a review of the potential benefits of LA in HEIs, the current implementation status and the underlying drivers for its implementation. The techniques for conducting LA and data needed for LA are then discussed. The challenges encountered in LA implementation in HEIs are highlighted next. Some frameworks proposed in the literature to assess the maturity of implementation of VLE and then specifically, LA in VLE are reviewed so as to identify the gap in the literature and highlight the contribution of this study.

2.1 Definition of learning analytics

Learning analytics basically involves the use of evidence and data generated from the education learning environments so as to enhance learning. Ferguson (2012) observed that LA began to coalesce as a discipline of its own around 2010. As such, several definitions of LA exist in the literature drawing from a wide range of disciplines (including education, psychology, philosophy, sociology, linguistics, learning sciences, statistics, intelligence and computer machine learning/artificial science). Brown (2011, p. 2) defined LA as “the metacognitive component, allowing individuals and institutions to understand learning and make informed decisions about resource allocations and required interventions to promote learner success”. One of the most cited definitions is the Society for Learning Analytics Research (SoLAR) definition of LA as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Long and Siemens, 2011, p. 33). Based on the SoLAR definition, the underlying aim of LA is to facilitate understanding and optimisation of learning and the learning environment (Vishwakarma et al., 2014) as shown in **Figure 2-1**.



Source: adapted from Vishwakarma et al., 2014

Figure 2-1: LA process uses data to improve learning

As depicted in **Figure 2-1**, the LA process starts from the data created from the learning system (VLE, LMS). This generated data from the learning environments is measured and analysed in order to make sense of it; creating new insight and knowledge about the learners and their learning environment. Different data analysis methods can be employed at this stage to better understand the data created from the interaction of the learner in the learning environments. The result of the analysis stage is the creating of knowledge that can be used to help improve the teaching and learning processes. The improvement to teaching/learning process gets utilised to enhance students learning experience. An improved learning environment then creates even more data as learners continue to interact with the learning system (Alenezi et al., 2018). HEIs are allowed to retain the data generated from the interaction of learners with the learning for statistical and research purposes for as long as possible; with appropriate safeguards in place to protect individuals (Information Commissioner' Office, 2020). The General Data Protection Regulation (GDPR) does not set a specific time limits for different types of data, instead, organisations have to make judgement on how long they need the data for their specified purposes (ibid).

Greller and Drachsler (2012) provide a holistic approach related to LA through identifying six critical dimensions: stakeholders; objective; data; instruments; external constraints; and internal limitations. The combination of these six dimensions is necessary to ensure an appropriate exploitation of LA in an educationally beneficial way. Zilvinskis et al. (2017) defined LA "as process of using live data collected to predict student success, promote intervention or support based on those predictions, and monitor the influence of that action". Zilvinskis et al. (2017) further distinguished LA into two critical components: level of analysis and intended audience. This approach is largely consistent with Greller and Drachsler's (2012) six dimensions approach to defining LA. In the critical component of level of analysis, Zilvinskis et al. (2017, p. 10) makes distinctions pertaining to the "level of analysis (student vs. class vs. curriculum); chronological characteristics of predictors (historical vs. contemporaneous), and type of outcomes (learning/behavior/development vs. retention/graduation)". This gives rise to different analytics distinguished as learning analytics, academic analytics, predictive analytics and learner analytics. For instance, academic analytics is perceived as the more holistic student support applications that focus more on student progress, persistence and completion which is not directly on learning (Long and Siemens, 2011) whilst learning analytics is perceived as narrow, focussing on engaging faculty in improving student learning within individual classes and programmatic curriculum (Zilvinskis et al., 2017). The two levels, however, are perceived as interrelated domains. Drawing on Van Barneveld et al.'s (2012) conceptual framework on analytics in HE, Zilvinskis et al. (2017) argue that predictive analytics can be employed in both domains (learning and academic analytics) in order to draw upon historical data so as to predict future outcomes which can facilitate interventions. Similarly, Pistilli (2017) defined learner analytics as the use of historical data from student records for prediction of outcomes of current students in order to identify students with a low likelihood of success for early intervention action. Predictive analytics is also useful where assessments have been cancelled and students' outcomes are determined based on historical data. This application has been observed during the Coronavirus pandemic (BBC, 2020). In this context, learner analytics and predictive analytics have a similar focus.

2.2 Learning Management Systems (LMSs) in HEIs

The increasing complexity and size of educational learning environments (Johnson et al., 2013) has made it imperative for specialised software-based systems to be developed in order to support the learning processes. These systems are commonly referred to as learning management systems (LMSs). A modern LMS is basically a software application used for the management and presentation of various learning contents; this includes all types of educational context such as courses, documents and videos. Particularly, an LMS allows remote access, retrieval and management of learning materials. Thus, the concept of LMS emerged directly from e-learning; which is multimedia learning using electronic educational technology (Mayer and Mayer, 2005). LMSs are anchored on four major axes: interaction, introspection, innovation and integration (Osma et al., 2016). Interaction enables communication processes among participants to be established whilst introspection is meant to enhance critical and creative thinking through the resources offered (ibid). Innovation is necessary as alternative learning and assessment processes increase. The LMS should also have an integration of communication between collaborative work and administration tools (Osma et al., 2016). Similarly, to be an effective LMS, Cano and Garca (2015) identified three main features: (i) it should be a fully developed environment that allows network access and interaction between learners and teachers; (ii) it possesses a set of resources and assessment strategies; and (iii) it provides activity management. Aydin and Tirkes (2010) contend that an advanced LMS needs to satisfy the following requirements: perform file management tasks; be totally or partly modular; have reusable content; have content creation and distribution tools and supporting applications; be extensible; and support multiple languages. Istambul (2016) adds that LMSs should take into consideration the behaviour of students in order to facilitate individualised learning; where students learn independently, accessing information for knowledge construction. Other requirements for an effective LMS include support for different user roles, such as tutors, learners, and administrators, facilitating assessment and tests, and handling heterogeneous content (i.e. text, images, video) (Osma et al., 2016).

There are many benefits of using an LMS in a HEI, Mafuna and Wadesango (2012) provide a set of benefits of LMS such as remote access to material at any time, self-paced learning and flexibility. This represents a key motivation for having a fully functioning LMS in this contemporary educational context where learners are more self-directed and independent in their learning (Duval et al., 2017). Thus, to be successful in the contemporary educational contexts, HEIs have to meet the increasing demand for self-directed and independent learning. These are key tenets for technology enhanced learning (TeL); which focuses on “how we learn and teach with interactive technologies, and how to design and evaluate effective technologies for learning” (Zimmerman and Schunk, 2001, p. 18).

Given their importance, LMSs are extensively used in HEIs particularly in developed countries (Reid, 2019; Veletsianos et al., 2013). As such, the HE market is well-provided with various types of LMSs. There are over 550 companies that offer LMS software (Fadil and Khaldi, 2020) in a market expected to be worth over USD15.72 billion in 2021 (Marketsandmarkets, 2020, p. 1). This represents around 19.6% compound annual growth rate (CAGR) from 2018. The major drivers for this exponential growth rate include "increasing adoption of digital learning, growing inclination toward bring your own device policy and enterprise mobility, extensive government initiatives for the growth of LMS, growing usage of artificial intelligence (AI) and machine learning (ML) in LMS is increasing the significance of eLearning in corporate and academic setups" (Marketsandmarkets, 2020). The most popular in the English-speaking HE market are Blackboard, Moodle, Brightspace (formerly Desire2Learn), Instructure Canvas, Edmodo and Sakai. Typically, these systems support mobile learning and online/offline synchronisation (Wright et al., 2014).

However, many of the developing countries are still struggling to catch up with their developed counterparts in the best use of LMS. Reasons behind the lag in LMS adoption are numerous, with inadequate information and communications technology (ICT) and infrastructure development being the primary contributors. In the case of Kuwait, which is the field study case country, LMSs have not had better chances than those of other developing countries. LMSs' presence is confined to a relatively small number of institutions and limited uses in HE (Al-Hunaiyyan et al., 2018). LMSs have not been utilised to satisfactory levels that justify its costs. Ahmed (2013) argues that among the many reasons why LMSs have failed in HE in the country are the high cost of technology, and the lack of effective (if any) business strategies. Nonetheless, the situation is rapidly changing.

2.3 VLE implementation in higher education institutions

Virtual learning is an integral part of the learning process (JISC, 2019; McAvinia, 2016). Virtual learning is usually associated with the concept of a Virtual Learning Environment (VLE), which is an electronic platform that facilitates learning and communication among learners and teachers. The Joint Information Systems Committee (JISC) (2019, p. 5) define VLE as:

> A collection of integrated tools enabling the management of online learning, providing a delivery mechanism, student tracking, assessment and access to resources. These integrated tools may be one product (e.g. BlackBoard, WebCT) or an integrated set of individual, perhaps open-source, tools.

The JISC definition provides a wide scope to incorporate new technological innovation despite McAvinia's (2016) criticism of the definition as prioritising course management. McMullin's (2005, p. 8) description of VLE as "a web-based platform supporting a more or less integrated suite of tools to support online learning" resonates more with the JISC definition. Other definitions have been offered in the literature with some emphasis on various aspects e.g. learning experiences. In this respect, Stiles (2007) offered a more learning experience focussed description of VLEs as providing facilities to manage the learning experience through interactions of tutors and learners.

However, McAvinia (2016, p. 19) argues that Stiles' definition seems "to place the communication element of the VLE ahead of its capacity to store and distribute course materials". The communicative elements of VLE has also been emphasised by others (e.g. Jennings, 2005; Stanley, 2009) in which VLE is perceived as facilitating interaction between learners and teachers. This emphasis on the communicative element is towards promoting a more student-centred approach. The presence of computer-mediated communication tools in the VLE makes this interactive process more effective and efficient; supporting collaborative learning. The tools include blogs, wikis, forums and messaging, among others (McAvinia, 2016). Thus, the embedded interactive process in the virtual space makes the learning experience real. The collaboration among learners can be synchronous (e.g. blogs) or asynchronous (e.g. email).

2.3.1 Features of virtual learning environment

In order to facilitate and support a complete online learning and teaching experience, VLEs have a number of features and tools. Thus, despite the emphasis of different functions of the VLE, there is some consistency regarding the features that a VLE should have. The underlying consideration in the design of the VLE is the need to consider a wide range of users and the need to support a variety of tasks and communications (Parsons, 2017). Achieving this underlying objective, however, is not straight forward and can be complicated. The common features and tools include content delivery, communication tools, assessment and administrative features (JISC, 2019).

Content delivery relates to the provision of study materials and learning resources to learners, who can then access and study at their own time. In addition to content delivery, VLE have embedded communication tools that enable the interaction between learners and tutors/teachers. This communicative feature provides support for students and assist to create a 'virtual' community among users that can be geographically separated. As indicated above, this communicative element is a key feature for a collaborative VLE which makes it more student centred (Stanley, 2009). The communication between users could be synchronous, using chat, audio and video conferencing or asynchronous using emails and discussion boards.

Some VLEs offer opportunities for learners to assess their understanding of the study materials through some form of student assessment. These are usually formative assessment (e.g. multiple-choice assessment) with automated marketing and immediate feedback. Such a feature is key in promoting self-regulated or independent study (Wong et al., 2019). The other common feature is the administrative feature which offers management and tracking of students. Administrative feature could include accessibility (passwords, usernames), calendars, general information about courses, announcements, assessment performance analysis, specific user tools (web pages, electronic diaries). Thus, the VLE provides a unified platform for content delivery, communications, assessment, and course management; with interface to the HE's central information systems and resources further increasing its functionality (Alhogail and Mirza, 2011; Stiles, 2007). These aspects have been acknowledged by McAvinia (2016) who also highlights the importance of security and privavy of the VLEs in facilitating online activities and interaction between learners and lecturers.

2.3.2 Virtual learning environment implementation overview

The earliest implementation of VLE in HEIs can be traced back to the late 1990s to early 2000s when systems such as WebCT and Lotus LearningSpace begun to appear (Stiles, 2007). The drivers for the early adopters of VLEs in the late 1990s were learner centeredness, pedagogic change, diversification, and coping with large numbers of students (Stiles, 2007). Some identified common drivers for adoption included: enhancing the quality of teaching and learning; improving access to learning for students off campus; widening participation/inclusiveness; student expectations; improving access for part-time students; and using technology to deliver e-learning (JISC, 2003; Stiles, 2007). Some identified constraints to full implementation included lack of time, money, academic staff knowledge, academic staff development and support staff (JISC, 2003).

By 2010, almost 100% of US universities and colleges were reported to have a VLE (McAvinia, 2016; Van Rooij, 2011). Brown (2010) indicated that almost 99% of UK HEIs had implemented VLEs. One of the drivers for the continued growth was the level of use by other HEIs which made it imperative to have VLE in order to compete and meet increasing demands for students.

Since then, VLEs have been extensively implemented in HEIs around the world (Browne and Jenkins, 2003; McAvinia, 2016; Stiles, 2007). These are redefining the way HEIs handle teaching, learning and assessment (Boulton et al., 2018; JISC, 2016), providing a means to structure, manage and deliver learning activities and contents in many HEIs around the world (Fincham et al., 2019). VLEs are now an integral part of HEIs. However, Lee (2017) argues that HEIs now need to move the focus from providing access to university education to increasing the quality of provision. LA offers such an opportunity through enhancing understanding and optimisation of learning services (Broadbent and Poon, 2015; Viberg et al., 2018). The importance of considering this increased use of VLEs and LMSs, which can be integrated with Student Information Systems (SISs), is that it has resulted in HEIs accessing or collecting student data that could be used to better understand and optimise learning and the environments within which it occurs. The next section discusses HEIs' learning services.

2.4 Learning services in HEIs

The term 'learning services' could imply different things. In a more traditional sense, the term refers to the different support and enhancing services that should be provided to the key stakeholders (i.e. academic staff, administration staff and students) who are involved in an education programme (Alenezi, 2018). These services offered by a HEI aim to aid the learning process, and include teaching contents, classrooms, libraries, research facilities and so on (Siemens, 2013). The learning process is conceptualised as comprising of review and planning, curriculum development and course delivery (Sclatter et al., 2016; Viberg et al., 2018). The learning services help to facilitate the learning process for contribution to knowledge advancement (i.e. education).

Learning services have developed to reflect learning provided as an online service following the introduction of online learning (i.e. eLearning). In this sense, an eLearning service provided by a HEI is an online service that enables a learner to access learning materials and/or interact with the teachers and other peer students (Alenezi, 2018). Sangra et al. (2012, p. 19) define eLearning as:

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

Siemens (2013) argues that eLearning has significantly contributed to the growth of LA; helping to make student data collectible and accessible for analysis. ELearning services include course management, content management, scheduling, personalisation, resource harvesting, games, simulation and podcasting among others (Dagger et al., 2007).

An improvement in learning services could contribute to development in different aspects of the learning environment, such as student retention, student performance and institution competitive advantage due the interconnection between learning services and the learning environment (Alenezi, 2018). This interconnection between the different components is depicted in **Figure 2-2**. This is a potential contribution for LA as it can help with improvements to learning services. The effective utilisation of LA in HEIs forms a key factor to the realisation of the improvements to the learning services (Ferguson, 2012; Strang, 2017). The improvement to learning services would then translate into enhancing student learning experiences. Thus, there is an identifiable causal relationship between LA, learning services and student learning experiences (Reimann, 2015; Salmons, 2019). The increasing quantity of analysable educational data has fostered the growth in LA that has provided some useful insights on students' performance, engagement and experiences (Baker and Siemens, 2014; Reimann, 2015). Understanding the learning services to which LA has potential to make an improvement to is, thus, necessary.

Understanding the different dimensions of learning services forms a basis for defining the key services that VLEs need to be effective in (Piccoli et al., 2001). In the learning services, teaching materials and resource management services are the core of the VLEs. These host and facilitate the dissemination of the content developed by lecturers to students. This service comprises three main areas: design, content and support management. Further, previous studies have demonstrated the importance of design in promoting and/or accelerating the learning process (Hong et al., 2002; Martínez-Torres et al., 2008; Whisenand and Dunphy, 2019; Wixom and Todd, 2005). The second area, content management services, has been established as one of the main influencers in the effectiveness of eLearning by several studies (Fayyoumi and Elia, 2015; McAvinia, 2016; McMullin, 2005) and hence, are at the centre of learning VLEs and platforms. Finally, support services are the pillars that sustain the content, such as e-library and catalogue, and IT support (Fayyoumi and Elia, 2015).

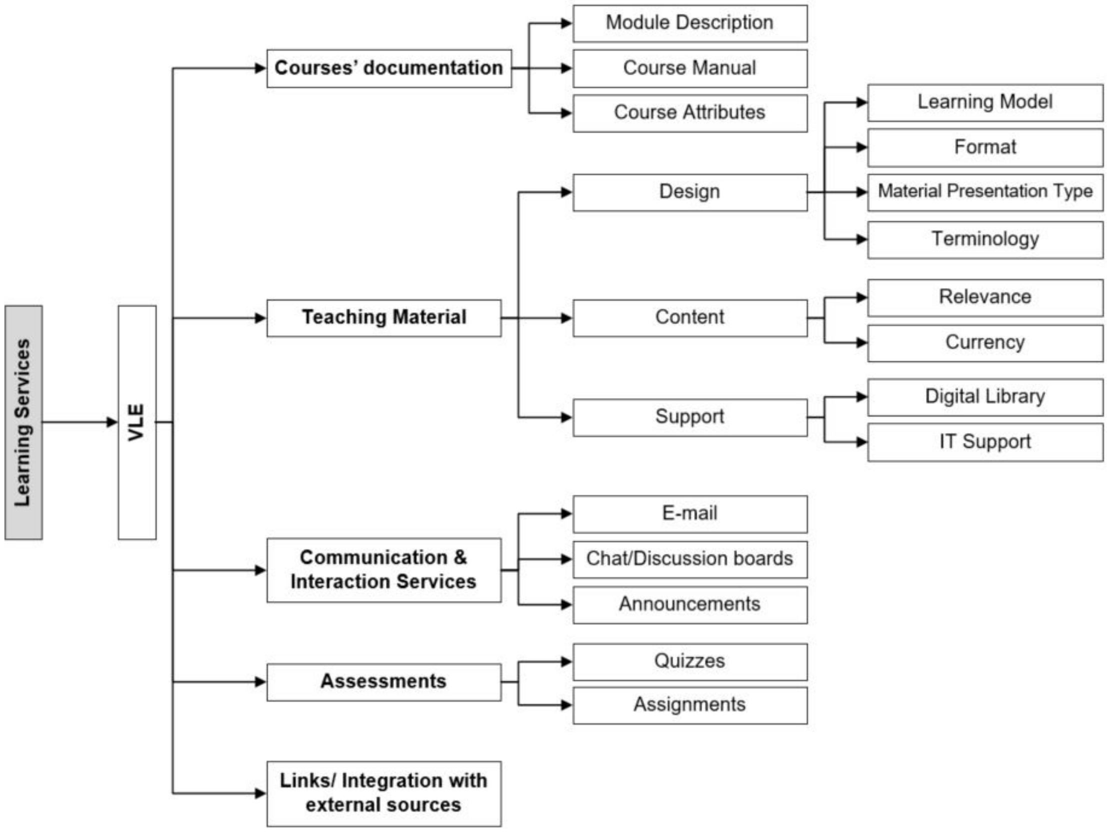


Figure 2-2: Learning services related to various aspects of the VLE.

Assessments services have been a recurrent theme of analysis in several studies (Sun et al., 2008; Islam, 2013). Assessment feedback has been identified as one of the most important components of the learning process (Henderson et al., 2019). Thus, the integration of assessment services within the VLEs helps improve the learning process through provision of both formative and summative feedback (Deeley, 2018).

The human learning process is highly rooted in the interactions and communication with others in order to conceptualise, discuss and apprehend knowledge from different perspectives (Jonassen and Land, 2014; Wong et al., 2019). Therefore, VLEs need to have embedded communication and Interactive facilities that simulate the natural and physical processes present in classrooms or informal learning environments (Rodríguez Ribón et al., 2015; Pattanasith et al., 2015). Communication and interactions are, thus, a major theme in eLearning and analytics studies. These encompass wikis, email, chat, dashboards, whiteboards, announcements, resources among others (Alhogail and Mirza, 2011; McAvinia, 2016; Pattanasith et al., 2015; Stiles, 2007). It is through the communication and interactive processes that a ‘virtual’ community of users is created.

As highlighted in section 2.2 and 2.3, the increasing use of VLEs and LMSs have made it easier for HEIs to access or collect large amount of data about learners and their learning environment. Each time that students/learners engage with the various components of the learning services, they leave a digital footprint. This is what accumulates into ‘big data’ (Aguilar et al., 2019; Waheed et al., 2020). This data can be exploited to better understand students and the learning process. LA provides this opportunity to exploit this rich data from the learning environment in order to improve teaching and learning. In other words, LA is a process of using the increased availability of datasets; around students’ activity, students’ progress, the learning context and other digital footprints lefts by students in the learning environment, in order to improve learning and teaching (Alexander et al., 2019; Larrabee Sønderlund et al., 2019; Sclater et al., 2016; Waheed et al., 2020). The potential contribution of LA to learning services is discussed next.

2.5 Potential contribution of LA to learning services

The key concern of LA is the utilisation of insights gathered from (students) data in order to make interventions that improve learning, and also generate actionable intelligence which informs appropriate interventions (Campbell et al., 2007; Clow, 2013). Thus, the implementation of LA in HEIs is driven by the objective of improving or enhancing student success (Arroway et al., 2016). This focus on learning differentiates LA from institutional analytics which is more concerned with improving services and business practices (Arroway et al., 2016; Dawson and Siemens, 2014). The need to enhance student success has been compounded by several factors which include: increasingly stringent accreditation practices; growing interest in performance funding models; concerns around financial aid practices and student debt; and the need to prepare graduates for the workforce (Arroway et al., 2016; Ewell, 2013). These factors make the imperative to adopt LA in HEIs in order to meet the demands strong.

The institutional investment in LA to improve student success arises from LA's potential to improve student retention, improving student course-level performance, and decreasing time to degree (Arroway et al., 2016; Larrabee Sønderlund et al., 2019). Besides student success, LA has potential to contribute to institutional effectiveness; providing institutions with an opportunity to create a cohesive, holistic argument in support of LA implementation (Ronald and Arroway, 2015). The contribution to improving the effectiveness of learning arise because LA helps enhance customization of the learning process and content; provision of students with information about their performance and of their colleagues and suggesting activities that address identified knowledge gaps; and providing academic staff with information of students who need additional help; which teaching practices are having more effects that are positive, among others (Siemens et al., 2011; Shacklock, 2016).

Thus, the implementation of LA in HEIs is directed at improving learning and teaching delivery. The implementation of LA can, therefore, be perceived as a proactive approach to monitor and understand learners and also the barriers to student learning. For instance, Waheed et al. (2020) showed that clickstream data from the VLEs can predict at-risk students for early intervention. Log data generated by the interaction of learners and the learning system of HEIs provide a rich source of data for LA (Nistor and Hernández-Garcíac, 2018). This data is generated by actions on the system conducted by a learner, including but not limited to click or page view counts, keyboard strokes, time spent on an activity, results of an action (such as results of a test taken on the system), and counts of other actions on the systems (Henrie et al., 2018).

For instance, Tseng et al. (2016) argue that they were able to classify Massive Open Online Course (MOOC) learners into three classes based on the data generated by those learners. These are active learners who actively participated in discussion forums and watched the videos most frequently, passive learners who watched the videos but did not participate in forums, and bystanders who were registered learners but their total activity was below a low threshold. The results shown by Tseng et al. reveal a positive association between the type of learner and their performance on the course. For example, active learners showed a higher completion rate and a better grade on the course. This class was followed by passive learners in terms of performance, while bystanders came last. The study concluded that feedback by instructors on forums could enhance students' engagement in courses.

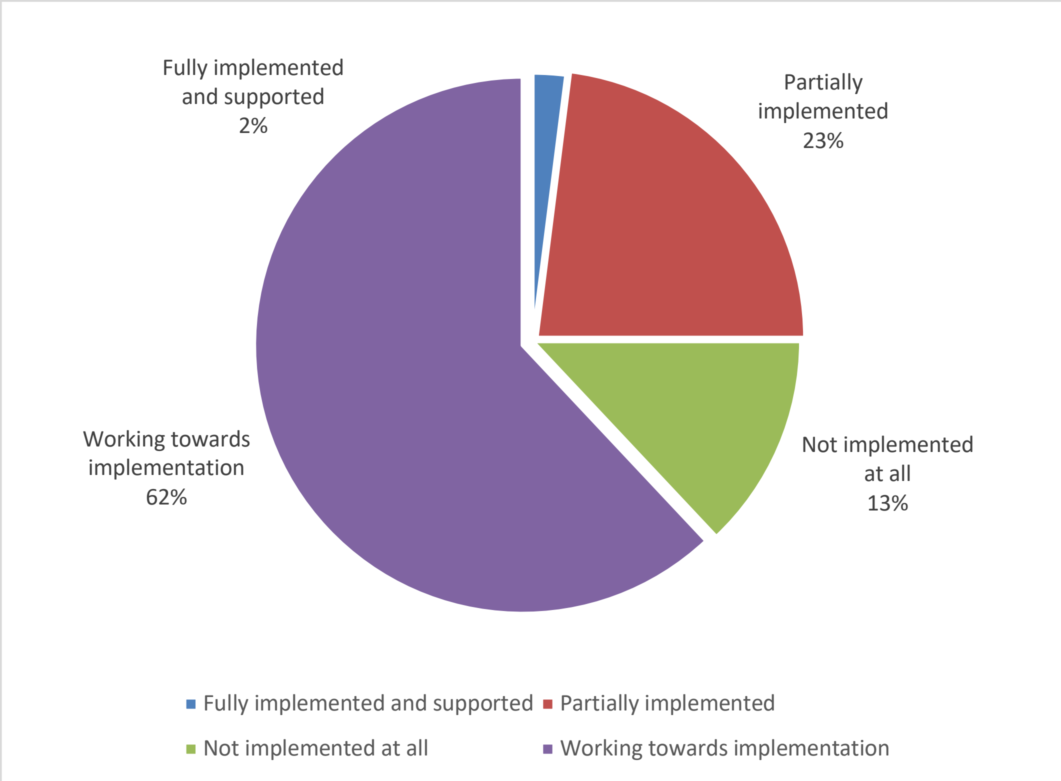
The effective utilisation of LA in VLEs that forms a key factor to the realisation of the improvements to the learning services. The desired improvements essentially justify embarking on an LA implementation project. When implemented successfully, LA could make significant contributions as (i) a tool for quality assurance and quality improvement; (ii) a tool for boosting retention rates; (iii) tool for assessing and acting upon differential outcomes among the student population; and (iv) an enabler for the development and introduction of adaptive learning (Sclatter et al., 2016, p. 5).

2.6 Status of LA implementation in HEIs

Despite the potential benefits to teaching and learning process that LA could provide, it is still generally underutilised in HEIs (Alexander et al., 2019; Parnell et al., 2018; Sclater and Mullan, 2017). This underutilisation of LA (including the lack of implementation) requires as a first step, the presence of an effective and efficient VLE to set the necessary conditions for the full functionality of LA (Leitner et al., 2017).

With particular reference to the United Kingdom (UK), LA is still in its earliest stages, and most institutions have not yet deployed a full LA system but use a variety of platforms, methods and other metrics (Ferguson and Clow, 2017; Shacklock, 2016). In other cases, some HE institutions prioritize LA at the departmental or unit level rather than considering it an institutional initiative (Arroway et al., 2016). Putting this into context, Newland et al. (2015) reported that nearly half of the UK HEIs had not implemented LA at all, with just one institution reported to have fully implemented a supported LA within the institution. Further, for those HEIs working with or towards LA systems, there was often no consistent approach adopted within the institution itself (Higher Education Commission, 2016). In another review of LA implementation in the UK, Arroway et al. (2016) found that HEIs more commonly use LA data in conventional ways to measure student progress rather than to predict success or prescribe intervention strategies which are indicators of true LA.

However, the LA implementation has significantly changed; generally improving. For instance, a significant improvement was observed in the number of HEIs in the UK working towards implementation or having partially implemented LA from 2015 to 2017. In particular, the HEIs that were working towards implementation of LA had nearly doubled from 34% in 2015 to 66% in 2017 whilst those that had partially implemented LA increased by 5% from 17% to 23% in 2017 (Newland and Trueman, 2017). Further, the percentage of HEIs that had not implemented LA at all had dramatically decreased from 47% to 13% (ibid) (see **Figure 2-3**). These results were based on 53 responses from HEIs in the UK who are members of Heads of eLearning Forum (HeLF). A critique could be raised that this survey isn't representative of the total universities in the United Kingdom (currently at 164). This would put the sample size at 32% based on the 2017-18 figure of 164 HEIs in the UK registered with the Higher Education Statistics Agency (HESA) (HESA, 2020). However, not all university have membership with HeLF which pushes the response rate to 39%. Further, this is the most recent survey carried out so far in the UK. Based on this progression, it can be concluded that the UK is beginning to wake up to the possibilities that LA provides (Higher Education Commission, 2016).



Source: Newland and Trueman, 2017

Figure 2-3: Overview of implementation of LA in UK HEIs

The LA implementation landscape is not static and will continue to change. As Newland and Trueman (2017) showed, significant progress had been made over a 2 year period from 2015 to 2017. Its rational to assume, in the lack of a national survey, that more progress has been made over the 2 years since 2017. The next section identifies the drivers for LA implementation.

2.7 Drivers for learning analytics implementation

There are several drivers that explain the growth in LA implementation. Ferguson (2012) identified two drivers (online learning and political concerns):

- Online learning

  The growth in online learning have led to the growth in big data in education. Online learning popularity has increased because of the benefits that it offers to learners. Some identified common drivers for providing online education included: enhancing the quality of teaching and learning; improving access to learning for students off campus; widening participation/inclusiveness; student expectations; improving access for part-time students; and using technology to deliver e-learning (JISC, 2003; Stiles, 2007).

  However, Mazza and Mimitrova (2004) argue that online education has the disadvantage of promoting student loneliness due to decreased contact with friends or teachers, and students may become confused in the online space, encounter technical issues or their motivation diminishing entirely. In other cases, students may find it hard to understand and assess the learning and quality of involvement of individuals, particularly in highly collaborative spaces with a lot of students.

- Political concerns

  Ferguson (2012) argues that there is a high demand for HEIs to measure, establish and develop performance. In the UK, the Quality Assurance Agency for Higher Education (QAA) is responsible for safeguarding standards in HE and seeks improvements in quality. The QAA monitors HEIs' own internal procedures for maintaining quality. As such, HEIs must have systems in place to monitor teaching performance at the point of delivery, and to deal with weaknesses in competence (QAA, 2017). The implementation of LA in HEIs is directed at improving learning and teaching delivery. Therefore, it is a proactive approach to monitor and understand learners and also the barriers to student learning in order to address quality.

Other drivers have been attributed to the growth in LA. Newland and Trueman (2017) identified leadership as the key driving factor in enabling LA development followed by increase in knowledge/understanding of LA. In other cases, the implementation of LA by other HEIs forced other HEIs to follow. Responses in Newland and Trueman's (2017) survey on drivers found the following as key contributors in their order of importance: leadership; increase of knowledge/understanding; clear objectives; funding, and clear ownership.

Shacklock (2016) argues that "the drivers for implementing LA are not only shaping how programmes operate presently, but also how they will continue to operate in the future". Further, Sclater et al. (2016) highlight that several drivers are making it imperative for HEIs to obtain value from the rich data sources that they are building about learners. These factors include:

> Increasingly stretched university budgets and a need for evidence based prioritisation of spending. While student fee income has to some extent alleviated financial pressures in English higher education, strong incentives remain to deploy resources spent on learning and teaching as efficiently and effectively as possible. Meanwhile students, as consumers, will increasingly, and justifiably, expect to be able to see evidence that their fees are being spent appropriately. (Sclater et al., 2016)

As a result, HEIs have to implement LA in order to meet increasing demands from the different stakeholders. Arroway et al. (2016) identified the need to enhance student success and institutional effectiveness as the primary drivers for LA implementation.

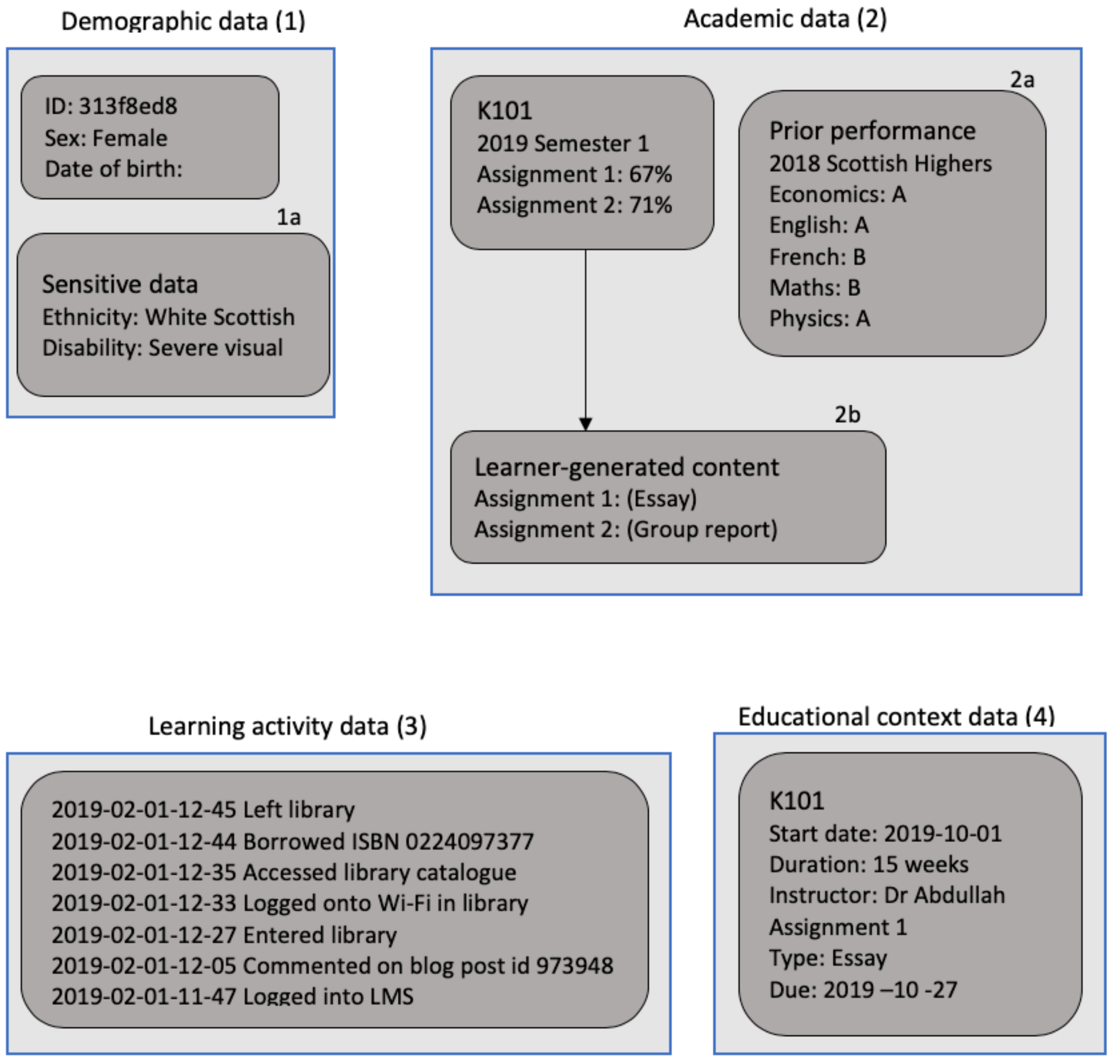
2.8 The required data to perform Learning analytics

There are various types of data that VLEs acquire about learners and the learning processes which can be used to extract valuable knowledge that can drive improvements in learning services. This rich data is often left unexploited, raising the question: how can such data be utilised in a way that can lead to improving learning? LA provides a valuable opportunity for understanding and optimising learning and the environments in which it occurs (Siemens and Gasevic, 2012).

Data can be broadly categorised into two groups: static data and fluid data (Shacklock (2016) as follows:

- Static data is basically the data generated and stored by the institution since its commencement, which includes student records (names, addresses, and grades), staff details, course information, financial records, admissions and applications data, alumni data, and estates and facilities data.
- Fluid data is data of a digital nature, also known as the 'digital footprint'- the data that generated as students interact with the university through the online systems and on-campus technology. Such data include login times, length of time stayed, page clicks, downloads, and comments left. Video and audio lectures also produce data, such as how long a student spends on a single audio/video file, how often they replay/rewind/fast-forward the file, and at what points they stop the file. Similarly, library visits generate data, such as how many books a student is borrowing, what books are borrowed often, how many times a book is renewed, what books are borrowed together, the relation between the books borrowed and student course, the time spent in the library, etc. This also includes the digital library which generate more data such as the pages browsed and the time spent on, the speed at which they read and the comments left if this option is available, among others.

Both of these data types contribute to analysable data for LA. Beyond the broad categorisation, Sclater (2017) suggests that data from the VLEs could be categorised into four different types: (1) demographic; (2) academic; (3) learning activity, and (4) educational context data. LA usually uses academic, learning activity and educational context data (2, 3 and 4). These categories are graphically shown in **Figure 2-4**.



Source: adapted from Sclater, 2017

Figure 2-4: Examples of learning analytics data

Demographic data could include sex, age, ethnicity, disability whilst academic data would include academic performance in assignments and exams, including prior performances. Learning activity data could include library usage, blog activity, learning management system logs among others while educational context data could include data regarding modules/courses, assignment types and dates, durations and instructors/tutor details.

Data could also be classified based on its origin. Based on the origin, data could be classified as:

(1) provided data - which are supplied by individuals;
(2) observed data - which are obtained automatically, for example by online forms;
(3) derived data - which are obtained from other data for example by calculating sums, and
(4) inferred data - which are generated by analytics to find correlations among datasets (Nistor and Hernández-Garcíac, 2018; Sclater, 2017).

LA usually uses types (2), (3) and (4). Some examples of LA data and their types are provided in **Table 2-1**.

Table 2-1: Examples of learning analytics data

Data	Type*
Student gender, date of birth	Type 1
How much time a student spends in a course	Type 3
Student input - forum / assignments	Type 2
How frequently they log in to the course	Type 3
Direct queries to the database	Type 4
Experience Application Program Interface (xAPI) Learning Data. xAPI is an eLearning system specification that allows tracking learning data	Type 2 / Type 3
Patterns of student activity	Type 4
Student success	Type 2
Student satisfaction	Type 4
Key Performance Indicators (KPIs) for learning performance	Type 2
Student engagement	Type 3 / Type 4
Login data	Type 3
Course activity	Type 3
Time a student first clicks on something in the course until he or she clicks outside the course or logs out	Type 3
Student performance	Type 4
Course access flag	Type 3
Fail to access system within a defined number of days	Type 3
Class average comparisons	Type 4
Missed deadlines	Type 2
Grade performance	Type 2 / Type 4
Attrition rates (dropping out)	Type 4
Ratio of instructor posts to student posts	Type 4
*demographic (1), academic (2), learning activity (3), and educational context data (4). Learning analytics usually uses types (2), (3) and (4)	

The techniques for analysing data are discussed next.

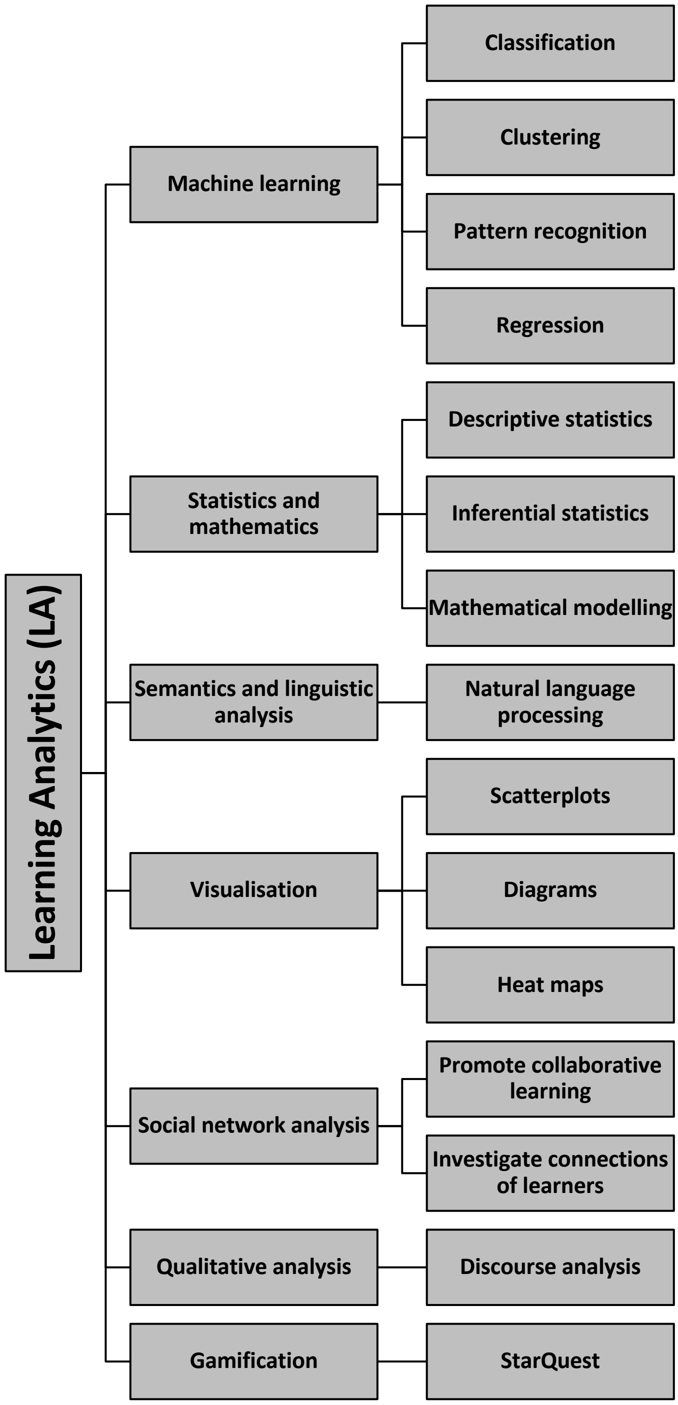
2.9 Learning analytics techniques and tools

LA deploys a set of pedagogical and technical methods and tools adopted from different disciplines such as statistics, machine learning and education. These different LA techniques of data analysis range from relatively simple to more complicated ones. Each technique serves a specific purpose and therefore, its application in the HEI would be towards achieving the related objective. Thus, the underlying aim of the data analysis, among other factors, influences the specific technique adopted. Some of these techniques include machine learning techniques, data and text mining, statistics and mathematics, semantics and linguistic analysis, visualisation, social network analysis, qualitative analysis and gamification (Nistor and Hernández-Garcíac, 2018; Sclater, 2017). These are discussed next:

- Machine learning techniques: machine learning techniques are methods for finding hidden information or knowledge typically within large amounts of data. The processes involved in these techniques include classification, clustering, pattern recognition, and regression, among many others. For example, classification can be used to identify students who attempt to trick the system (Pardos et al., 2013).
- Data and text mining: methods and techniques that allow finding hidden information or knowledge in large textual files. Data mining techniques can be used in text mining to detect and extract knowledge from textual contexts. For example, written feedback given to students on their assignments can be analysed to extract knowledge using text mining.
- Statistics and mathematics: descriptive statistical tools can help summarise large amounts of data in order to facilitate their analysis. This also includes inferential statistics, which allow deducing certain properties of the analysed data. Mathematical modelling can also be used in the analysis of data. Accordingly, models are created to summarise large amounts of data by truncating variables that are considered irrelevant, which help predict values of other variables with little or no information about.

- Semantics and linguistic analysis: the analysis of the use of language in a given context, including natural language processing. For example, using linguistic analysis to parse student posts for prediction purposes (Joksimović et al., 2015). Linguistic analysis forms the basis for text analysis. Semantic analysis helps to capture the real meaning of any text in a given context.
- Visualisation: the presentation of data (in this case large amounts of data) in visual formats which allows for easier human recognition. This technique is currently gaining interest because of its promising ability to provide results that are recognisable by the human eye. In learning analytics, visualisation can be used, for instance, to represent the attrition rate in a MOOC (Xing and Du, 2019).
- Social network analysis: the analysis of information found on social networks. The analysis can use various tools and consider any number of variables. For example, in learning analytics, social networking can be used to promote collaborative learning and the analysis is thus used to investigate interconnections of learners, teachers and resources.
- Qualitative analysis: this describes the analysis of material of qualitative nature. For example, discourse analysis or the analysis of discussion forums in a MOOC, where students discuss certain topics, can provide important data for analytics.
- Gamification: the act of applying game design and concepts to a non-gaming context, in this case learning, for the purpose of conveying learning in a more entertaining manner. For example, a gamification system called StarQuest used by the University of Coventry in the UK analyses user behaviour and measures performance levels based on cooperation, competition, and contextual parameters (de Freitas et al., 2017).

Figure 2-5 provides a graphical presentation of these techniques.



Source: adapted from Khalil and Ebner, 2016

Figure 2-5: Methods and techniques for Learning Analytics

There are various tools available for LA which could be applied by HEIs to obtain and conduct LA. The predictive analytics reporting (PAR) framework provides a useful reference regarding the type (level) of analytics being conducted in an organisation (ie. descriptive, diagnostic, predictive, and prescriptive) (Newland et al., 2015). The Gartner Analytics Ascendancy model helps to show the ranking of the different types of analytics based on value and difficult (Wiraeus and Creelman, 2019). Using the four analytic types, Sampson (2017) classifies analytics tools according to the types of the analytics conducted. Some examples of descriptive analytics tools identified included SmartKlass and the LA Enhanced Rubric; predictive analytics tools included the Early Warning System and the Engagement Analytics tool; and prescriptive analytics tools included the LearnSmart tool, developed by McGraw-Hill Education, and the Adaptive Quiz tool. **Table 2-1** provides examples of some tools classified based on the tool types.

Table 2-1: Examples of Tools used for LA in some HEIs

Tool Type	Available Applications	Description	Learning Development Framework
Reporting	Blackboard, Moodle, Canvas	Individual user tracking, course based	Individual and group monitoring
Social network analysis	SNAPP - Social Networks Adapting Pedagogical Practice	Extracts and visualises student relationships established through participation in learning management system discussions	Social-constructivist models of learning
Student dashboards and monitoring	SAM - Student Activity Monitor, Student Success System	Visualises student activity for promotion of self-regulated learning processes	Self-regulated learning – monitoring of individual behaviours and achievements to guide the learning process
Individual and group monitoring	GLASS - Gradient's Learning Analytics System, PASS – Personalised Adaptive Study Success	Visualises student and group online event activity	Individual and group monitoring
Learning content interaction	LOCO-Analyst, Panopto	Provides insight into individual and group interactions with the learning content	Individual and cohort monitoring
Discourse analysis	Cohere	Supports and displays social and conceptual networks and connections	Social learning and argumentation theory

Source: Gasevic et al., 2019; Lockyer et al., 2013; Sclater et al., 2016; Viberg et al., 2018

Table 2-1 shows some of the available tools for LA classified based on what LA aspect(s) the tool offers. For example, discourse analysis could include the analysis of written or verbal feedback from tutors, social network analysis provides information from social interaction of students, tutors or both, and reporting contributes to keeping track of individual students. Some of the available applications for each type of tool are included in the table with a brief description. The last right column provides some frameworks or theoretical models used for the development of the respective applications. Several learning theories exist which can be applied to educational technological (in this case, LA) to better understand the influence on learner. Pinner (2011) argues that VLEs have an implied constructivist pedagogical approach since they provide “a place to collaborate and extend discussions rather than merely hosting trackable learning objectives” (p. 6). The usage, however, may still be behaviourist. Wong et al. (2019) identified self-regulated learning and social constructionism as the most employed theories in LA studies. These are identifiable in **Table 2-1.**

The above methods and tools can be used individually or in combination during the analytics process. There are some issues associated with these tools and techniques, which are mainly related to the complexity of using them. This is manifested in the need, for example, for specialised systems, such as learning content interaction or discourse analysis systems, which are not normally part of the LA or LMS system and are able to carry out these tasks required. These techniques also require expertise in the disciplines, which might not be necessarily available in the HEI. Therefore, the institution may find itself required to choose certain techniques feasible to the available system. The choice of a certain technique or set of techniques could be a hard decision to make, which would need to take into consider many variables, in addition to the physical limitations of the existing systems that an organisation uses.

In addition, the use of the above tools for exploiting data, however, raises questions related to the ability of the organisation to keep up with security, privacy and ethical considerations (see section 2.11). Privacy is concerned with identifying and accordingly protecting private data when collecting, analysing, and using the data for LA. There are also questions about the security of the data and the ability of the organisation in establishing secure communication and storage channels for these data. Another issue is related to transparency of the used data and its ownership. These and other related issues must be properly addressed in order to maintain a proper and sustainable LA project in an organisation. The EU General Data Protection Regulation (GDPR) provides rules for data privacy and regulates the way organisations approach data privacy.

2.10 Stakeholders in LA in HEIs

The importance of stakeholders' interaction and engagement for the successful implementation of LA in VLE has been widely acknowledged in the literature (Dollinger et al., 2019; Greller and Drachsler, 2012; Hommel et al., 2019; Khalil and Ebner, 2015). The need for involvement of stakeholders in LA implementation arises partly because the implementation process has several challenges (i.e. technical, financial, organisational and ethical) that need to be overcome. Through the involvement of different institutional stakeholders, some of the challenges could be mitigated (Khalil and Ebner, 2015; Tsai et al., 2019). The emphasis of LA is on learners and their learning environment (Long and Siemens, 2011). As such, the stakeholders in LA are those that contribute to the learning process.

Three groups in typical educational institutions; academic staff, academic support staff and students form the key actors involved in the learning process (Wong, 2017). In particular, these actors are involved in three elements of the learning process cycle: review and planning, curriculum development and course delivery (Tlili et al., 2019). Each of these actors has an important contribution to the learning process and thus, the focus on these actors in the development of the maturity framework (see chapter 5) in this research. The involvement in the learning process of these stakeholders include:

(i) Academic staff: review and planning of academic programmes, curriculum development and learning outcomes, course delivery and assessment learning, arranging external speakers, as well as continuous improvement.

(ii) Academic support staff: help in admission and registration process, course management, timetabling, space allocations, support the management of virtual learning environment, oversee student academic progress and support graduation ceremony.

(iii) Students: learning, assessment, feedback, learning path customisation.

Having established the contribution of the three actors to the learning process in higher education institutions, the next section discusses common challenges encountered in the implementation of LA in HEIs.

2.11 Challenges of learning analytics implementation in HEIs

Whilst increasing evidence has been provided that LA helps improve learning support and teaching in HEIs (Ferguson, 2012; Ferguson and Clow, 2017; Hommel et al., 2019; Tsai et al., 2019; Viberg et al., 2018), many challenges exist that hinder its efficient exploitation. Ferguson (2012, p. 8) highlighted the challenges associated with "building stronger connections between LA and learning sciences, developing methods for working with a wide range of datasets for improving learning environments and focusing on the perspectives of learners and ethics". Other inhibitors to implementation include the different views of stakeholders regarding the vision and the methods to use to achieve the set goals (Khalil and Ebner, 2015). The challenges can be categorised in general as technical, financial, organisational and ethical (Chatti et al., 2014; Herodotou et al., 2019; Tsai and Gasevic, 2017) as depicted in **Figure 2-6**.

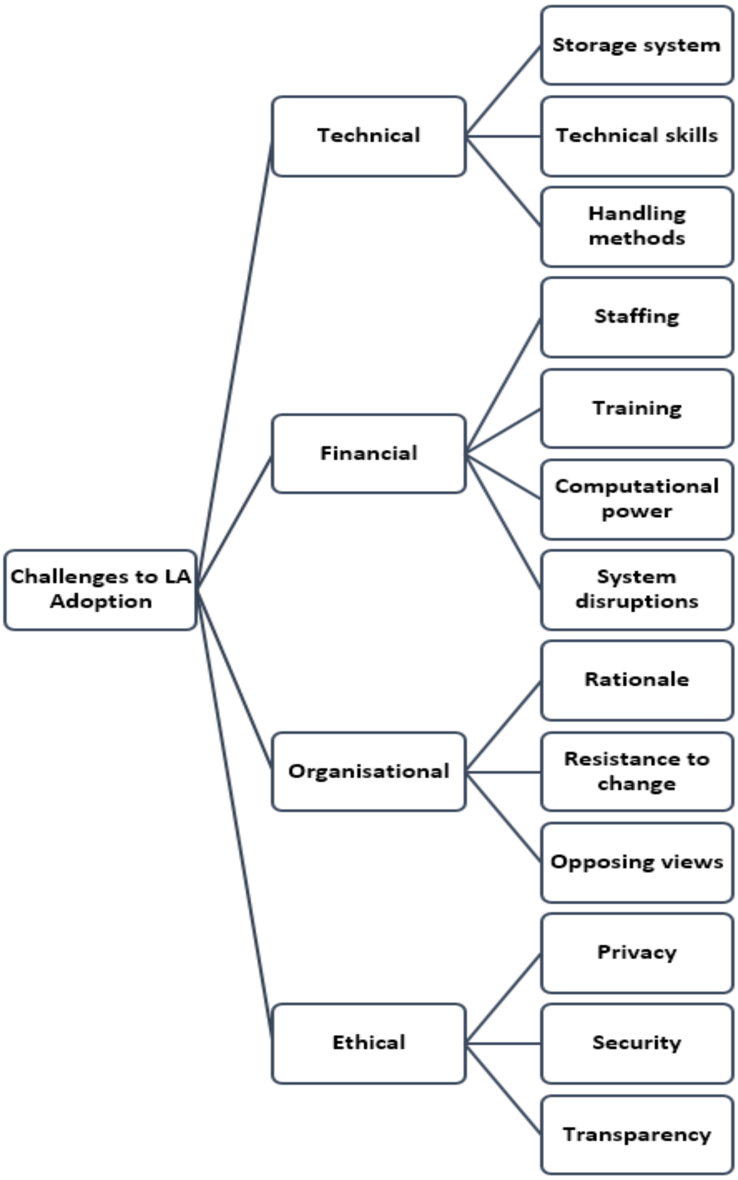


Figure 2-6: Technical, financial, organisational and ethical challenges in LA implementation

- Technical Challenges

  There are limitations related to the storage systems and analysis tools currently available for HEIs. Large amounts of data require advanced methods for their appropriate storage and analysis. These methods are still being developed and may not be feasible to HEIs (Najafabadi et al., 2015; Chatti et al., 2014). Moreover, the challenge also includes intrinsic factors related to the understanding of learning itself in order to optimise it by LA.

The complex and heterogeneous data produced are therefore, challenging in nature. Essentially, undertaking appropriate LA requires advanced skills in various fields such as computer science, statistics, machine learning, data mining, mathematical modelling, etc (Kay et al., 2013; Tervakari et al., 2013; Waite et al., 2013).

- Financial Challenges

  The costs of acquiring and carrying out learning analytics by an HEI are not in any means marginal. An LA project in an HE is typically expensive (Borden, 2018). As indicated earlier, trained personnel, computation and electronic storage equipment and facilities are requisites for learning analytics. These costs may frustrate some HEIs from delving into the LA realm when they prepare their return on Investment forecasts. Costs also include the computational power needed to run algorithms and obtain results (Govindarajan et al., 2016).

- Organisational Challenges

  The rationale of undertaking the LA project in a HEIs may not be convincing to the key stakeholders. Accordingly, it can be hard for the project initiator to attract enough funds. It may be difficult for the LA project initiators to prove to the shareholders what the benefits of such a project are as the results are usually not immediate (Dawson et al., 2014). This presents a serious organisational challenge. Like any other project, the LA project brings change to the organisation. Resistance to change may hence be inevitable (Ferguson et al., 2014). Change accompanying the LA project includes the overall institutional uptake by staff members, which is identified as one of the main stoppers of LA initiatives (Tsai and Gasevic, 2017). Therefore, the adopting organisation will need to carry out change management to minimise resistance and make the process as smooth as possible. This requires the involvement of leadership in consideration to the interests of various stakeholders (Shacklock, 2016).

- Ethical Challenges

  The ethical issue of the data collected for the purpose of learning analytics is a controversial one (Ferguson and Clow, 2017). The types of data, what they describe, how they will be presented, how to access them and many other issues need to be considered when LA is conducted. Privacy of the learners to whom the data belong is a main concern that needs addressing and clear understanding by the different parties dealing with the matter. According to Pardo and Siemens (2014), the ethical issues are tightly connected to concepts like accountability, transparency and trust. Some of the requirements for privacy assurance include security and open disclosure of surveillance, tracking mechanisms, and the legal and ethical dimensions of using the data. The EU General Data Protection Regulation (GDPR) provides rules for data privacy to regulate the way organisations approach data privacy.

2.12 Developing institutional capacity for implementation of LA

An HEI needs to develop its capacity in order to successfully implement and manage a LA project. The potential benefits of LA identified in section 2.5 would be more likely achievable when LA is fully implemented and adequately supported. Building the institutional capacity is basically providing a suitable environment for LA to be implemented and also to fully function (Arroway et al., 2016; Norris and Baer, 2013; Yanosky and Arroway, 2015). In this respect, consideration should be given to the different aspects that contribute to a LA project. Importantly, it's the combination of these aspects that contributes to the capacity to handle LA (Norris and Baer, 2013). The identified components that need to be developed to support LA implementation can be categorised as process, infrastructure, data and human resource and skills (Arroway et al., 2016; Boyer and Bonnin, 2016; Norris and Baer, 2013; Sclater et al., 2016; Sclater, 2017; Yanosky and Arroway, 2015). These components are depicted in **Figure 2-7** and discussed thereafter.

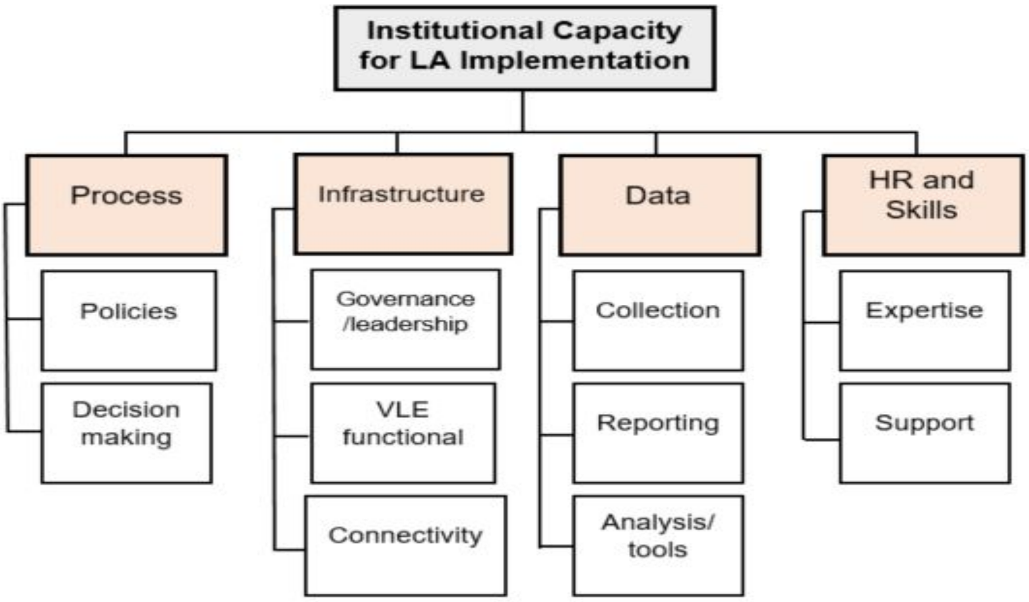


Figure 2-7: Institutional capacity for LA implementation

2.12.1 Process

An HEI's process comprises of policies and procedures that contribute to the learning and teaching process. The processes that an HEI puts in place has a significant contribution to the success of LA implementation. In order to achieve full LA functionality, the processes and practices need to be embedded or integrated into the culture and fabric of the institution and be used effectively by the key stakeholders (Norris and Baer, 2013).

The process component includes the policies and the decision-making culture of the institution. The decision-making culture includes the commitment of senior management to learning analytics and also the promotion of a technologically oriented culture where there is acceptance of learning analytics (Arroway et al., 2016). Policies related to data collection, access and use need to be clearly established and communicated to all stakeholders (Norris and Baer, 2013).

2.12.2 Infrastructure

Institutional capacity should be developed with respect to infrastructure that should support LA implementation. This includes the investment in technical infrastructure that includes analytics tools, applications, services and developing capacity to store, manage and analyse data (Arroway et al., 2016).

Important in this component is the enhanced functionality of the existing LMS or VLE that enables the data capture for the analytics tools to be applied on. Further, the increased functionality of the VLE/LMS also enables the possible integration of the analytical applications within the learning system.

Technological infrastructure, tools, and applications should support user connectivity and interaction with the learning system. This also involves having a reliable internet connectivity, a significant problem in emerging and developing country contexts (Asampana et al., 2017; Jackson and Fearon, 2014). Investment in infrastructure should be supported by management and an appropriate leadership oversight has to be established.

2.12.3 Data

HEIs also need to build their capability in term of their data efficacy (Norris and Baer, 2013). Data efficacy relates to the quality, standardisation and overall appropriateness or 'rightness' of data (Arroway et al., 2016) which is directly linked to its analysability using LA tools.

A fully functional VLE/LMS should have developed capability to collect the analysable data necessary for LA. The consideration by an HEI should be that the existing learning systems structure should enable users to access data that is analysable for decision making purposes. In this respect, it's not only about the easy of data capture, but also about data availability and accessibility.

An HEI should essentially have a "data-driven mind-set incorporated in processes" (Norris and Baer, 2013). The availability, accessibility and analysability of data makes the application of LA tools and software for reporting more productive. The application of the LA tools should enable reporting that is useful for decision making.

2.12.4 Human resources and skills

Another important component that an HEI should develop is its human resources and related expertise/skills (Boyer and Bonnin, 2016; Norris and Baer, 2013; Sclater et al., 2016). Human resources and skills are integral to the successful implementation of LA in an HEI (Shacklock, 2016). As such, an HEI must invest in human resource and skills development in order that an appropriate level of human resources and expertise is available. An appropriate level of expertise is needed to support two aspects: the undertaking of the analysis of the data from the VLE/LMS using the LA tools/applications; and the provision of technical support to users. Technical support, for instance, through training is needed to improve user confidence and acceptance (Asampana et al., 2017; Jackson and Fearon, 2014; Nawroth et al., 2015).

The importance of for HEIs to build this capacity was recognised by the Higher Education Commission (2016) which stated that "unless institutions and university staff are data-capable and equipped with the resources and skills to manage data well, HE will not be able to catch up and students will miss out on many potential learning and support benefits" (p.3). In order to build this capacity, HEIs need to equip their teaching and administrative staff with necessary skills to perform their roles in a digital, data-driven world (Shacklock, 2016). This involves providing appropriate training and support in order to improve and develop the staffs' digital capability and data management skills. In this respect, there must be investment in skills training to achieve an appropriate level of analytics staffing (Arroway et al., 2016).

2.13 Existing LA frameworks

The recognition of the benefits of LA to learning and teaching, and the challenges that underlie its efficient utilisation in HEI forms an important driver for the development of an institutional LA strategy (Shacklock, 2016). A LA strategy that considers key stakeholders in the process is needed for progression in LA application. One of the most comprehensive LA maturity assessment frameworks is the Educause maturity and deployment model (Alexander et al., 2019; Arroway et al., 2016). The Educause analytics maturity index assesses the overall institutional capability in LA; but not the specific competencies in LA. The aspects of LA assessed to gauge maturity are: decision-making culture, policies, data efficacy, investment and resources, technical infrastructure, and, institutional research involvement (Arroway et al., 2016; Yanosky and Arroway, 2015).
Based on the six (6) dimensions, the level of maturity of LA would then fall into five levels: (i) absent/ad hoc; (ii) repeatable; (iii) defined; (iv) managed and, (v) optimised (Sclater, 2017; Yanosky and Arroway, 2015). These are described in **Table 2-2**. Thus, an institutional readiness and progression can be classified according to these levels. The model has been employed in several studies (Mackney and Shields, 2019; Nsamba, 2019; Parnell et al., 2018).

Table 2-2: Educause higher education analytics maturity levels

Maturity Level	Description
Level 1 – Absent/ad hoc	We don't current have this capability, or we address it in an improvised, irregular way.
Level 2 - Repeatable	We have an established capability, but our practices are mostly informal.
Level 3 - Defined	We have a standardised capability and have documented procedures and/or responsibilities related to it.
Level 4 - Managed	We manage this capability to achieve predictable results on the basis of reliably measured performance indicators.
Level 4 - Optimised	Besides measuring performance, we regularly reassess the way we deliver this capability, in order to improve practices and manage risks.

The limitation of this maturity assessment framework arises from its institutional focus, instead of student (learner) focus. Yanosky and Arroway (2015) observed the investment prioritisation by HEI on this level of analytics than LA which is more learner focussed. In addition, whilst there are five levels in this model similar to the developed framework in this research, the scope in this research project is broader; focussing on user interactivity at each maturity level.

Another model, similar to the Educause maturity and deployment model, had earlier been developed by the Educause Centre for Analysis and Research (ECAR) called the 'ECAR Analytics maturity index for higher education' which was aimed at providing a starting point for understanding an institutions' progress in analytics along six dimensions (culture, process, data/reporting/tools, governance/infrastructure, investment and expertise) (Dahlstrom, 2016). The level of an institution in LA implementation would be evaluated for each dimension by a score ranging from 1 to 5 depicting the five levels (starting, visioning, launching, implementing and transforming). This maturity model has similar limitations to the Educause analytics maturity index in its wider institutional focus, not specific to LA in VLE and user interactivity.

Further, one model that has been used to gauge the implementation of LA is the Gartner analytics ascendancy model which helps to show the ranking of the different types of analytics based on value and difficult (Wiraeus and Creelman, 2019). This model is not specifically for HEIs but focusses more on the type of analysis. Greater value is obtained from data when it is used for predictive and prescriptive analysis where the aim is to understand what will happen and how to make it happen. The descriptive analytics stage is the basic level that uses data to answer the question ‘what happened?’. This is followed by diagnostic analytics which addresses the question of ‘why did it happen?’. The progression along the model is from basic information (descriptive analytics) to optimisation (prescriptive analytics).

Other maturity models have been suggested (Arnold et al., 2014; Chatti et al., 2012; De Freitas et al., 2015; Lias and Elias, 2011). For instance, Arnold et al. (2014) developed the Learning Analytics Readiness Instrument (LARI) which is an instrument aimed to assess LA project implementation readiness within an institution. The LARI can be used to help determine strengths and potential weaknesses of the institution before undertaking a large-scale LA initiative. Therefore, the LARI requires that the LA project has been initiated in order to work, and it has little use as a measure of readiness for a potential LA project. The limitation of the LARI, similar to the Educause maturity model is the larger institutional focus, not LA maturity within the existing VLE. The limitation in De Freitas et al.’s (2015) conception of LA model was the focus on only students despite the acknowledgment that LA is about learners and the learning environment. Other models focussed more on the application of LA in the VLE (Chatti et al., 2012; Lias and Elias, 2011; Siemens, 2013) without conceptualising the progression in the usage of LA. Chatti et al. (2012), for instance, proposed four dimensions in the implementation of LA: (i) what? (What kind of data is used in the analysis); (ii) who? (Who is the target of analysis); (iii) why? (What is the objective to be achieved by analysing the data collected); and (iv) how? (What techniques will be used to perform the analysis of the data collected?).

On the other hand, Lias and Elias (2011) identified four types of technology resource focus on the implementation of LA: computers, people, theory and organisations. In a review of LA implementation, Gašević et al. (2019) identified three major themes, namely, the development of predicators and indicators for various factors (e.g. academic performance, student engagement, and self-regulated learning skills); the use of visualizations to explore and interpret data and to prompt remedial actions; and the derivation of interventions to shape the learning environment. In developing the LA maturity framework in this paper, key stakeholders are considered which also recognises the complexity that underlie LA in VLE and the contextual nature of its application in different educational settings. As such, a multi-level conceptualisation becomes relevant which highlights progression from one stage/phase to another.

Other developments of maturity models have focussed on the VLE readiness (Duffy, 2016; Marshall and Mitchell, 2002). However, most of assessment of VLE maturity usually consider the software underlying the VLE rather than the VLE utilisation itself. For example, a standard maturity assessment model is Marshall and Mitchell's (2002) e-Learning Maturity Model. This model is based on the Capability Maturity Model (CMM), which is a process model in software engineering that uses five levels to assess maturity of software of an organisation (Duffy, 2016). The assessment levels are learning, development, support, evaluation and organisation. Ajis et al. (2017) used this model to describe maturity of the VLE of a public HEI in Malaysia. Based on this model, Ajis et al. established a connection between the five levels and the learning processes in their target learning institution. Similarly, Herdianto and Bandung (2018) applied the model to assess e-learning development in HEIs in Indonesia.

User interactivity in VLE is an importance consideration in the development of a maturity model in this study. In this context, Wankel and Hinrichs (2012) argue that the development of VLEs in terms of technology is outstripping its development in terms of user interaction, particularly in teaching and learning. Similarly, Saleeb and Dafoulas (2012) content that a complete VLE that attains a high-quality realistic, immersive real-time environment while maintaining the level of interactivity required to carry out adequately intricate real-world tasks like learning and teaching is not currently possible. On the contrary, the existence of a high level of realistic details makes an environment unbelievable or unconvincing to users (Drettakis et al., 2007; Appleton and Lovett, 2005). Thus, an assessment of VLE maturity should be considered within a wider scope which involves the user interactivity within the VLE. As such, key stakeholder engagement forms an important element in establishing a maturity assessment. Therefore, users' level of interaction with the VLE forms the main component of the maturity framework development in this study. One of the main limitations of most existing VLE maturity models is that they do not have learners as a key aspect of the assessment, rendering maturity as a measurable element, which is rather flawed because of the lack of targeted user interactivity. This study makes a contribution in this aspect by considering user interactivity in the development of the maturity framework.

2.14 Research Gap

The review of maturity models or framework above has shown that there exists a gap in the literature regarding LA in VLEs maturity assessment in HEIs.

- Some models, for instance, the Gartner analytics ascendancy model are not specifically formulated for HEIs despite their relevance to understanding the types of analytics.
- The ECAR maturity index, whilst specific to HEIs does not focus specifically on VLEs and the interaction of the key stakeholders (i.e. academic staff, academic support staff and students) within the learning services.
- The importance of assessing the level of LA implementation (LA maturity) forms an integral step to realising, not only the LA underutilisation, but also gives insight to how development to full functionality or maturity can be achieved. The assessment of the maturity level of LA in VLE is necessary as it would enable HEIs to evaluate their progression to the realisation of the full benefits of a functional LA.

- The maturity assessment framework (see chapter 5) takes into consideration the key stakeholders and how they interact with learning services at different levels of maturity. This has largely not been considered in existing models.

Thus, this study makes an important contribution to the LA literature.

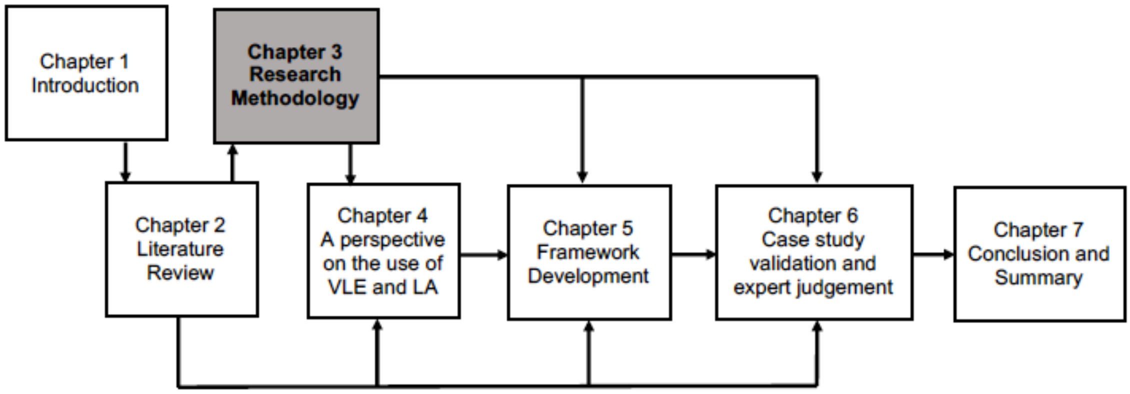
2.15 Summary

This chapter was aimed at reviewing the literature on LA. It started by giving some context through definitions highlighting the multidisciplinary nature of LA. There is no universally accepted definition of LA. The drivers for LA adoption in HEIs were identified as the increased demand for online learning and political concerns. Leadership and increased knowledge of LA are also pushing the growing implementation of LA in HEIs in the UK.

Whilst LA has potential to contribute to teaching and learning improvements, through offering additional insights about learners and their learning environment, there are technical, financial, organisation and ethical issues that still need to be overcome.

The chapter also reviewed some LA maturity frameworks and models such as the Gartner analytics ascendancy model, ECAR Analytics maturity index and Educause student success maturity. Whilst these provide an insight to LA implementations, they do not explicitly cover LA in VLE in HEIs which is the focus and contribution of this study. The next chapter outlines the methodological approach to the development of the LA maturity framework.

3 RESEARCH METHODOLOGY



3.0 Introduction

This chapter outlines the methodological framework developed in order to address the research objectives. In presenting this methodological framework, the chapter outlines the philosophical and theoretical perspectives underpinning the development of the LA maturity assessment framework and discusses the multi-phases methodological approach adopted.

3.1 Methodological overview

This research draws on the contextual lens (see, Vygotsky, 1978) that views learning as contextually bound and a result of social interactions (Wong et al., 2019). Within this contextual lens is the recognition that the learning process is inherently subjective, and context bound. Also, that learners have a significant role to play in the learning process, having the ability to develop or influence their understanding through interactions. It is the interaction of learners and their learning environment (VLEs) that results in rich data that could be utilised to better understand the students and improve the learning process. Because of the complex nature of the learning process; influenced by contextual factors (including ICT), the study adopts a multi-phases research methodology to develop understanding in order to develop a LA maturity framework. This approach considers explicitly the complex nature of the learning situations in which educational technology is applied (Issroff and Scanlon, 2002).

A multi-phases research methodology, thus, recognises learning as a complex issue (Phillips, 2014). In addition, the adopted multi-phases research methodology results in a multi-theoretical perspective in which more than one learning theory is applicable. In this context, theoretical perspectives arising from contextual lens become relevant. These theories include some learning theories that have been advanced in the literature which include social learning theory, social constructivism, self-regulated learning and connectivism (Jonassen and Land, 2014). Therefore, the study takes a multi-theoretical perspective that recognises the dynamic landscape of educational technology and the multi-disciplinary nature of LA. This approach acknowledges that each of the different learning theories gives a theoretical lens that could be employed to better understand the learning process through the application of educational technologies. **Table 3-1** gives an overview of the philosophical perspectives and methodological choices.

The universal rule applicable in the development of this methodological framework is that the adopted research strategy and the methods employed must be appropriate to address the research questions (Creswell, 2013; Collis and Hussey, 2013). As such, the developed multi-phases methodological framework was influenced by the need to address sufficiently, the four research questions outlined in section 1.3.

A clearly outlined methodological framework is important, not only for the possible replication and constructive criticism that could arise from it (Robson and McCartan, 2016) but also for establishing a basis for logical and valid reasoning. Thus, in developing the multi-phases methodological framework, important consideration was made to how each of the different phases in the methodological framework contributed to the research objectives and overall research aim. In doing this, it was necessary to start with a wider understanding of learning and the learning process, and the role of educational technology in the learning process. Such a wider understanding required knowledge of the philosophical and theoretical perspective surrounding the learning process and how educational technology contributes. Thus, like any other research, this research also “brings with it a set of assumptions about the social world it investigates” (Denscombe, 1998). In this respect, the role of LA in VLEs to influence improvements to the learning services is underlined by assumptions to how learning occurs.

The ontological assumptions (which refer to the nature of reality and existence) which underlie LA is that subjective, multiple realities exist in some constant change. Individuals construct reality through their interactions. These realities are also sustained through social practices. In the construction of these realities, some patterns of social action are sustained whilst others are excluded (Burr, 2015). This is what enables the use of educational technology (in this case, LA), to study learners’ behaviour. Further, the individual realities are influenced or affected by social factors (Knight et al., 2014). In addition, the epistemological assumption is that the interaction of learners in the learning environment creates (more) information which can be translated into knowledge through LA. It’s the process of interaction through the learning environment (VLEs, LMSs) that more information is generated which can be analysed to obtain knowledge.

Further, a multi-theoretical perspective informed by contextual lens theories have influenced this research. The relevance of learning theories application to LA is that they “help to convert information from learning analytics into actionable knowledge for instructional and learning design” (Wong et al., 2019, p. 38). These theories are important, not only because they aid explanation of the phenomenon of learning but also because design principles for learning environment, materials and tasks can be derived from the theories (Ertmer and Newby, 2013; Murphy and Knight, 2016).

Other methodological choices include the nature of the different research phases in the multi-phases methodological framework (see section 3.4) as being exploratory, descriptive, explanatory and also evaluative (see section 3.2). In addition, both qualitative and quantitative approaches are employed using a case study strategy. The qualitative approach employed semi-structured interviews whilst quantitative approach used online questionnaires (see section 3.4.2). The sampling approach was purposive directed at key VLE stakeholders. Grounded theory technique (Dougherty, 2017) was utilized in the analysis of qualitative data whilst statistical analysis was performed on quantitative data. Further, the time horizon for this research is cross-sectional. These methodological choices are utilized at different phases of the multi-phases methodological framework (see section 3.4).

Table 3-1: Summary of philosophical perspectives and methodological choices

Ontology	Subjective, multiple realities
Epistemology	Knowledge is contextually bound, affecting by social factors through interactions (socially constructed)
Theoretical	Multi-theoretical perspective informed by contextual lens theories
Purpose	Exploratory, descriptive, explanatory and evaluative
Approach	Multi-phases research methodology employing both qualitative and quantitative techniques
Strategy	Case study strategy
Time horizon	Cross-sectional
Sampling approach	Purposive sampling
Method and data	Primary data Semi-structure interviews online questionnaires
Data analysis	Statistical analysis of quantitative data Grounded theory analysis of qualitative data

Before outlining the multi-phases methodological framework employed in this study, additional context is developed by discussing the purpose of research in the next section followed by the country context of Kuwait where the field study was conducted.

3.2 Purpose of research

The purpose of research can be exploratory, descriptive, explanatory or policy oriented/evaluative (Gray, 2019; Silverman, 2016). This different phases in the multi-phases methodological framework serve different research purpose. However, the overall research project is largely exploratory and descriptive in nature.

Thus, in developing a maturity assessment framework for LA in VLE, an exploration is needed of the current utilisation of VLE and LA implementation, including key aspects/elements that indicate readiness. This understanding is useful in designing and developing a maturity assessment model, establishing performance measurement tools that could be applied and describing a road map recommendation that could be followed to advance the LA implementation.

3.3 Research context - Kuwait

As the study involved a field study conducted in Kuwait, a brief contextual background of the country is relevant.

Kuwait is an oil rich country located in the north-western corner of the Persian Gulf boarded by Iraq and Saudi Arabia. The country is estimated to have 8% of the world's oil reserves (Statista, 2020). Since the discovery of oil in the 1930s, the country has mainly been oil dependent. Oil rents contribute to over half of the country's gross domestic product (GDP), 92% of export revenues and 90% of government income (CIA, 2020).

The country is largely a desert with an area of only 6,880 square miles and a population of 4.14 million whose life expectancy is around 76 years (World Bank, 2020). With a gross national income (GNI) per capita of USD34,290, Kuwait is one of the high-income countries in the World (World Bank, 2020). Unemployment rate is low at only 2.2% in 2019 with the public sector employing over 74% of the labour force (CIA, 2020).

The country's annual GDP growth rates was 1.25% in 2018 (2.9% in 2016) whilst its inflation has declined from 10.6% in 2008 to 0.5% in 2018 (World Bank, 2020). With respect to its political context, Kuwait was a former British protectorate that gained independence in 1961 (BBC, 2018). It's a constitutional emirate with a semi-democratic political system (CIA, 2010). In terms of governance scores, the country scores low with respect to voice and accountability indicators but high in terms of rule of law and control of corruption (World Governance Indicator, 2020). Appendix D gives additional geographical, economic and political context of the country.

In terms of the adult literacy rate, the country has high literacy rate of 96%, representing a significant rise from 78% in 1995 (World Bank, 2020). The significant high literacy rate is attributed to free education being offered to all citizens regardless of gender, at all the levels of state education, including higher education (Ministry of Education, 2020) with scholarships offered to pursue higher education outside the country to deserving students. There are currently four state-supported higher education institutions namely: Kuwait University, The Public Authority for Applied Education and Training (PAAET), Higher Institute for Theatre Arts and Higher Institute of Music Arts (Ministry of Education, 2020). The Kuwait University is the oldest among these, established in 1966 while PAAET in 1982 in order to fill the gap for vocational and technical training needs (PAAET, 2020). PAAET has the highest number of students (58,000) as compared to Kuwait University (41,000) (Arab Times, 2018; Ministry of Education, 2020). PAAET was the selected case study HEI in this research project. Kuwait, and PAAET, in particular was selected for it being an emerging country that is investing significantly in higher education, with the HEI having a high and growing number of students, and also because of the researcher's accessibility.

The multi-phases research methodology framework, outlining the detailed phases of this research project, is presented next.

3.4 Multi-phases research methodology

The multi-phases research methodology developed for this research has been influenced by the research aim and the underlying research questions. The focus is on adopting appropriate research tools and methods that enable the research questions to be sufficiently addressed (Creswell and Poth, 2016). As such, this research makes a methodological contribution in demonstrating the multi-phased process required in developing quality and valid research frameworks. The multi-phases methodological framework, shown in **Figure 3-1** consisted of 6 phases, each phase making a contribution to the research.

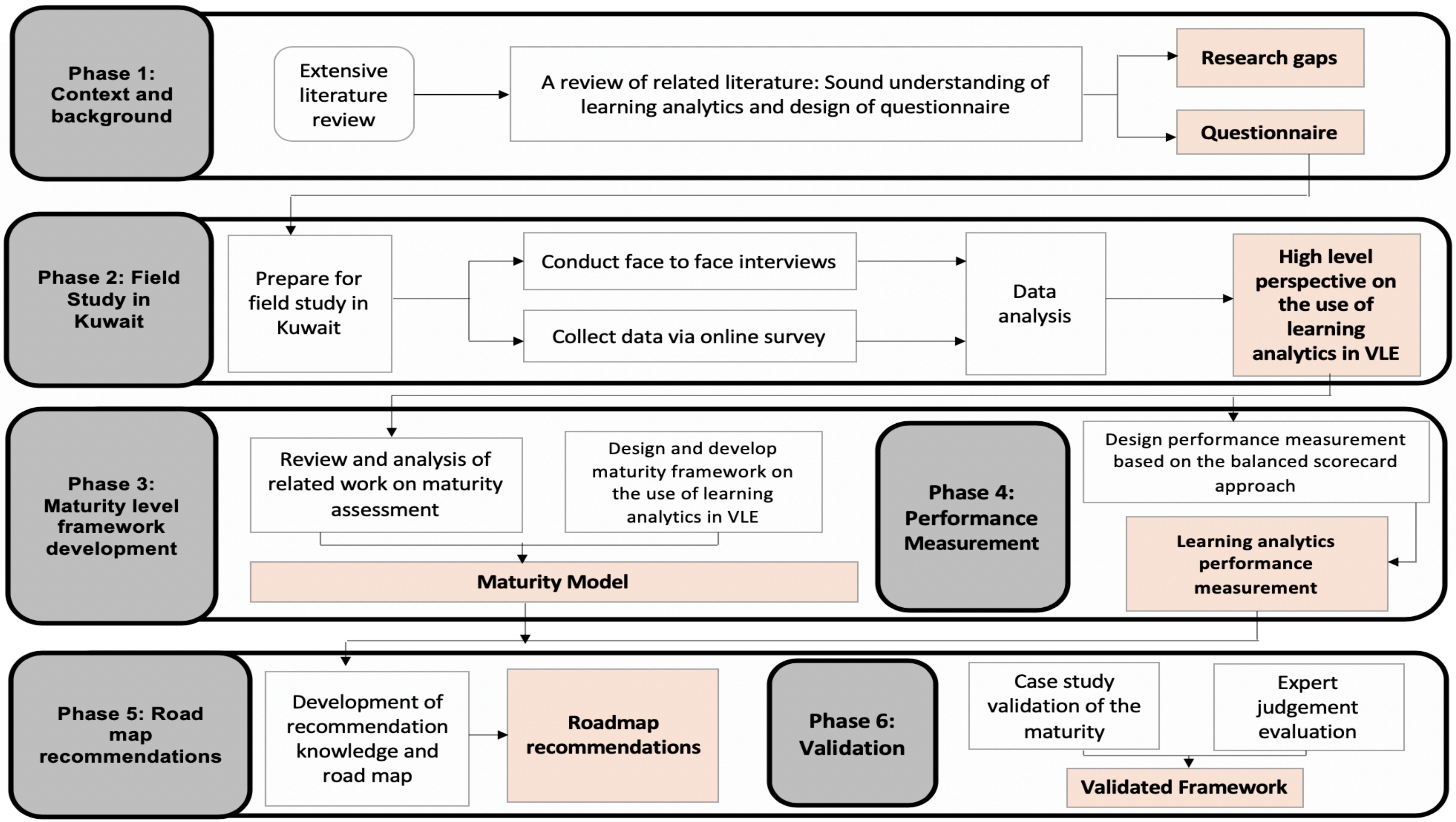


Figure 3-1: Multi-phases methodological framework

3.4.1 Phase 1: Understanding the context

The initial phase is aimed at gaining an understanding of the core context of the research through an extensive literature review presented in chapter 2. An extensive, systematic review of the literature was important for understanding the usage of LA in VLE and to capture good practices. In addition, it facilitated for the identification of the research gaps. This phase was also necessary as it aided the design of questionnaires and appropriate interview questions in readiness for the field study.

3.4.2 Phase 2: Field study

Phase two was a field study. A case study strategy was adopted. A case study research approach aids in obtaining a deeper investigation into the utilization of the VLE/LMS and the readiness/implementation of LA. A case study research strategy is basically an approach to "doing research which involves an investigation of a particular contemporary phenomenon within its real-life context using multiple sources of evidence" (Robson, 2002). According to Stake (2000), case study is of special interest as it is used to look for the detail of interaction within its contexts to provide an understanding of a particular circumstance; in this case, the utilization of LMS/VLE and implementation/readiness of LA. Further, Saunders et al. (2012) support that a case study strategy is often used in exploratory and explanatory types of research. As this research phase is exploratory and descriptive in nature, a case study approach assisted in finding out "what is happening; seek new insights; to ask questions and to assess a phenomena in a new light" (Robson, 2002) which makes this strategy appropriate in investigating the use of LMS/VLE and LA implementation/readiness.

Thus, employing a case study research approach, the field work phase was aimed at gaining a high-level perspective on the use and effectiveness of LMS/VLE and LA implementation/readiness in the HEI. Two methods were utilised in the field study: face to face interviews and online questionnaires. The face to face interviews were conducted with academic staff and academic support staff (part of the key stakeholders) from the Public Authority for Applied Education and Training (PAAET), one of the largest HEIs in the Middle East. The aim was to capture as many participant views as possible during the field study in order to gain a good understanding of the use of VLE/LMS in the HEI. In total, 14 academic and 3 academic support staff were successfully interviewed. This response number was significant and appropriate to achieve the research aim. Through conducting interviews with these participants, understanding was gained on the usage (and challenges) of LA in VLEs to support learning services in the education institutions.

The second part of the field study was targeted at learners/students since these are the intended beneficiaries from the LA; they are the key stakeholders. An online survey was conducted with the students on their use of VLE. In total, 135 students took part in the online survey. The field study helped to gain an overall perspective of the use of LA in VLE which was instrumental in the development of the maturity assessment framework.

3.4.3 Phase 3: Develop maturity levels model

This phase was the development of the maturity assessment model. In order to develop the model, the understanding gained from the field study and the extensive review of the literature was instrumental. The review of the literature on maturity of LA and the overall perspective gained from the field study helped to identify the core aspects in the development of an assessment framework. The literature review involved a review and analysis of related work on maturity assessment of LA, first in general and then specific to HEIs. This helped identify some reported good practices in LA and the existing lacuna on a maturity framework for LA in VLE in HEIs. A model of maturity level of LA in VLE for use in HEIs was then designed and developed (see section 5.1). The model developed consists of five levels: basic (level 1 – resource availability); developing (level 2 – system development); functional (level 3 – system functionality); advanced (level 4 – advanced functionality); and optimised (level 5 – process/system optimisation). These levels can help position the implementation of LA in VLE by HEIs. The levels are also a reflection of the developmental route that an institution can take in the implementation of LA. At each of these levels, the key education stakeholder groups will interact with LA in the VLE differently.

3.4.4 Phase 4: Develop performance measurement on learning analytics utilization

This phase was directed at designing and developing performance measurement metrics that form part of the maturity assessment framework. As such, the performance measurement metrics are meant to be used with the LA maturity level model. Using the performance measurement metrics within an HEI could give an indication as to level of maturity of LA within the institution. The performance measurement metrics was developed based on a balanced scorecard approach to measure aspects related to the process, infrastructure, data and human resource skills associated with VLE. The metrics involved key questions that could be addressed to HEIs in each of the identified four main aspects. The design and developed LA performance measurement tool is discussed in detail in section 5.2.

3.4.5 Phase 5: Roadmap recommendations

Phase 5 is aimed at utilising the developed LA maturity level model and the LA performance measurement tool in order to identify the progression route for an HEI in LA implementation and use this knowledge to make improvements. Thus, based on the understanding of the implementation of LA in VLE in HEIs, which is determined by using the performance measurement tool, the position of an HEI is mapped against the 5 maturity levels of the LA maturity level model. Then recommendations are drawn on the status of LA implementation and how this knowledge could be used to make improvements along the maturity levels.

Thus, the road map recommendations are meant to provide a guide to HEIs on the improvements that can be made in order to progress the institution towards a higher maturity level at which benefits of LA are more realisable. These road map recommendations form an integral part of the LA maturity assessment framework; as such, they have to be used in conjunction with the LA performance measurement tool and the LA maturity level model. The aim is guide progression so that LA implementation can fully support learning services improvements.

3.4.6 Phase 6: Validation of maturity assessment framework

This phase is directed at validating the developed LA maturity assessment framework (i.e. maturity level model, performance measurement tool and road map recommendations). This is an important phase in the development of a LA maturity assessment framework as it tests the validity or applicability of the framework to different institutional contexts. The validation of the LA maturity assessment framework was based on two approaches. The first approach involved case study strategy in which HEIs were selected in different educational (country) contexts. The aim here was to highlight the applicability of the framework to different institutional as well as educational and regional contexts. This is important as it shows the generalisability and universality of the framework. This perspective is also in cognisant of the contextual lens assumptions of the learning process.

The second approach to the framework validation was through utilising expert judgments. In this respect, the model was availed to different experts in LA to order to obtain their judgements and evaluate these judgments based on the underlying aim of the developed framework. This is an important aspect considering the nature of LA research as new field still in the early developmental stage.

The results from the framework validation gave an additional insight and improvements to the initial framework was made. The result is a validated LA maturity assessment framework. The implementation and results of this phase are discussed in chapter 6.

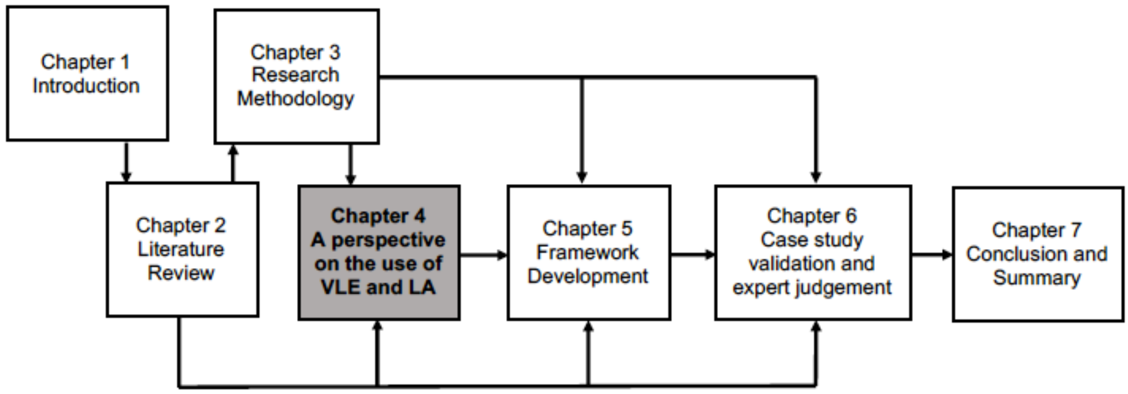
3.5 Summary

This chapter has presented the methodological framework that underlie this research aimed at developing a framework to assist HEIs in elevating their maturity level of employing LA in order to drive improvements in their learning services. The methodological framework has been influenced by the research objectives and the nature of LA in its intended contribution to learning services improvements.

The methodological framework developed adopts a multi-theoretical perspective that recognises the learning process as dynamic, fluid and interactional complex. Further, this perspective also acknowledges the multi-disciplinary nature of LA, which has developed from a dynamic landscape of the utilisation of educational technology for learning and teaching improvement. The methodological approach utilised to develop a LA maturity assessment framework is a multi-phases research methodology that involved 6 key phases of: context and background, field study, maturity level model development, performance measurement tool development, road map recommendations, and validation.

Research ethics have been considered throughout the research process. All data collected has been subsequently stored in a manner that maintains confidentiality and anonymity in line with the General Data Protection Regulation (GDPR). The effective employment of this methodological framework has enabled the attainment of the research aim; the development of a validated LA maturity assessment framework. The next chapter discusses the insight gained from the second phase of the multi-phases research methodology.

4 A PERSPECTIVE ON THE USE OF VIRTUAL LEARNING ENVIRONMENT AND LEARNING ANALYTICS



4.0 Introduction

This chapter is aimed at presenting the findings from the field study that was designed to gain a high-level perspective on the use of VLE/LMS and potential LA. This perspective was obtained from key stakeholders (students, academic staff, academic support staff) on their utilisation and effectiveness of VLE and the LA readiness and/or implementation. The perspectives of academic staff and academic support staff was obtained through interviews whilst that of students through online surveys. This research phase was largely exploratory in nature; to gain an understanding from the key users of the VLE/LMS. The next section gives details regarding the participants/respondents in the field study before presenting the results.

4.1 Participants/respondents

As highlighted in section 2.10, the key stakeholders of LA implementation are learners/students, academic staff and academic support staff. As such, this research targeted these three stakeholder groups. Further, the adoption of the research methods (questionnaires and semi-structured interviews) was largely influenced by the nature of these stakeholders.

4.1.1 Online survey

Thus, in order to obtain a better understanding of the use and effectiveness of the VLE/LMS from the students' perspective, the number of students involved needed to be large in order to capture a more realistic picture from this stakeholder group. As such, an online survey using questionnaires (see Appendix A.1) was conducted.

The questionnaire was designed based on a 5-point Likert scale from strongly agree to strongly disagree with a set of statements. The respondents had to pick only one option for each statement, reflecting how much they agreed (or disagreed) with each of the statements. The Likert scale method is commonly used in research based on surveys to gauge the participants' attitudes towards a phenomenon or situation expressed in simple and clear statements (Joshi et al., 2015). It is important to note that the scales of this type of analysis must be treated as ordinal not interval scales (Lietz, 2010). This means that differences in answers are not measured by distance but by the number of answers to each statement. The choice of the Likert scale helps draw robust quantitative analysis from the data obtained (Joshi et al., 2015).

The questions were short and precise designed to evaluate perspectives on the use and views of the VLE/LMS and its effectiveness. As such, student information such as age, sex or nationality was not necessary, and thus, not captured. The questionnaire was uploaded to Survey Monkey and a link generated available at: https://www.surveymonkey.co.uk/r/vrn8rkl.

In order to reach the students, an invitation was sent out to all students through their university email with the help of the College Dean. The email invitation gave information to the students about the research and directed them to the online survey link on Survey Monkey if they accepted the invitation. In total, 135 students from different courses at PAAET successfully completed the online questionnaires. This is useful as it enabled more views/perspectives to be captured from this stakeholder group. The two aspects/classes of information solicited through the questionnaire were the use and view of the learning management system and its effectiveness. **Table 4-1** shows the different aspects of the LMS/VLE that were assessed through the online survey to students. Thus, in analysing the results from the survey, these different aspects are investigated which helps show the adequacy/readiness of the existing LMS/VLE for possible LA implementation.

Table 4-1: Category of questions in the questionnaire

Question	Category
1. Sufficient learning resources for my study are available online	Availability
2. I can receive technical support on using the online system whenever needed	Technical support
3. The online system is user-friendly and accessible to students with minimal training	User friendliness/Simplicity
4. It is necessary to use the online learning system in order to progress on the course	Necessity
5. Academic staff encourage the use of the online learning system and make resources available online	Academic support, Availability
6. I feel I am able to use the online learning system confidently	User friendliness/Simplicity
7. The online learning system also includes interactive tools with peer students and staff	Collaboration
8. The online learning system works well and the layout and design are consistent and properly maintained	Functionality, Reliability, Aesthetics
9. The need of the online learning system is evident	Necessity
10. Using the online learning system has made my learning experience at the institution better	User friendliness, Learning experience
11. The online learning system serves its purpose well and its use is self-explanatory	Simplicity, User friendliness
12. The system's downtime is kept minimal	Reliability
13. The system's technical issues are kept minimal	Reliability, Technical Support
14. I trust that my data in the system are kept safe and private	Security, Privacy
15. I spend a considerable part of my study time on the system	Accessibility, Necessity

4.1.2 Face to face interviews

In gaining a deeper understanding of VLE utilisation and LA readiness/implementation from the other stakeholder groups (academic staff and academic support staff), semi-structured (face to face) interviews were necessary. The participants/respondents from these stakeholder groups were selected from the HEI, PAAET, in Kuwait. The PAAET is one of the largest HEIs in the Middle East with many students from countries around the world. This HEI provides a rich source for data collection owing to its position within the Middle East's education sector and also its growing investment in educational technology. In total, 14 academic and 3 academic support staff were interviewed (see **Table 4-2**). **Table 4-3** presents the position of the interviewees in the face to face semi-structured interviews.

4.1.3 Sampling technique

Purposeful sampling method was used in selecting the participants/respondents. This type of sampling is used to identify and select the highest value information sources based on the researcher's discretion. It also allows effective use of resources (Palinkas et al., 2015). Another key advantage of taking a purposive sampling approach is the increased willingness of the interviewees to participate in this research. This is because the participants are identified and selected based on qualities that they possess which puts them in a position of knowledge and/or experience. The interviewees were, therefore, identified first based on their availability and willingness to do the interview, and then based on the diversity of their positions and qualifications. The summary of participants/respondents is shown in **Table 4-2** whilst the position of interviewees is shown in **Table 4-3**.

Table 4-2: Number of participants according to stakeholder groups

Stakeholder group	Participants	Research method
Students	135	Online survey
Academic staff	14	Semi-structured interviews
Academic support staff	3	Semi-structured interviews
TOTAL	152	

Table 4-3: Position of interviewees

Position	Job type
Assistant Professor in the Department of Art Education at the College of Basic Education	Academic
Associate Professor of office technology	Academic
Assistant Professor, Department of Family and Consumer Sciences	Academic
Associate Professor in the Department of Civil Engineering, College of Technological Studies	Academic
Teaching staff member in the Department of Educational Technology	Academic
Assistant Professor in the Department of Mechanical Engineering (Manufacturing) in the College of Technological Studies	Academic
Assistant Professor, Department of Law, College of Business Studies	Academic
Chairman of the Promotions Committee	Academic
Chairman of the committee preparing the curriculum	Academic
Member of the teaching staff in the Department of Special Education	Academic
Dean of Community Service and Continuing Education	Academic
Assistant Professor, Department of Petroleum Engineering, College of Technological Studies	Academic
Associate Professor in the Department of Manufacturing Engineering Technology, College of Technological Studies	Academic
Member of the curriculum development committee	Academic
Head of Support and Support Unit at the Computer Centre	Administrator
Deputy Director of the Computer Centre	Administrator
Head of the Information Technology Unit at the Computer Technology Centre	Administrator

4.1.4 Data collection

The data collection started in May 2018. The Director of Legal Affairs (DoLA) at PAAET was the key gatekeeper (Broadhead and Rist, 1976; McFadyen and Rankin, 2016) for the research; The interviews were conducted at three sites, the Faculty of Business Studies, the College of Basic Education and the College of Technological Studies of PAAET. The duration of interviews was between 30-60 minutes. The interview guide used is shown in Appendix A.2.1.

The interviews were recorded on a Sony digital voice recorder and subsequently transcribed. The interviews were conducted in Arabic following the interview guide shown in Appendix A.2.2. The next section presents the findings from the analysis of data obtained from online questionnaires (quantitative analysis) and semi-structured interviews (qualitative analysis).

4.2 Quantitative Analysis

4.2.1 Approach to data analysis

The obtained data from 135 students was statistically analysed using Microsoft Excel and the statistical tool, Statistical Package for the Social Sciences (SPSS) to obtain inferential and descriptive statistics. Microsoft Excel was used to set up the data and then SPSS was used to run the regression and produce the charts. Descriptive statistics include measures of central tendency and measures of variability useful in summarising a given data set (MacRae, 2019). These help to describe and summarise the data obtained in a meaningful way. The inferential statistics, on the other hand, helps to measure whether the results obtained are significant or rather insignificant based on statistical parameters to help substantiate and generalise the results of the sample used to the targeted population (Amrhein et al., 2019). This includes estimation of parameters and testing of statistical hypotheses of possible relationships informed by a review of the literature on different aspects of the VLE/LMS.

The descriptive statistics of the data obtained from 135 students using a 5-point Likert scale questionnaire are presented first.

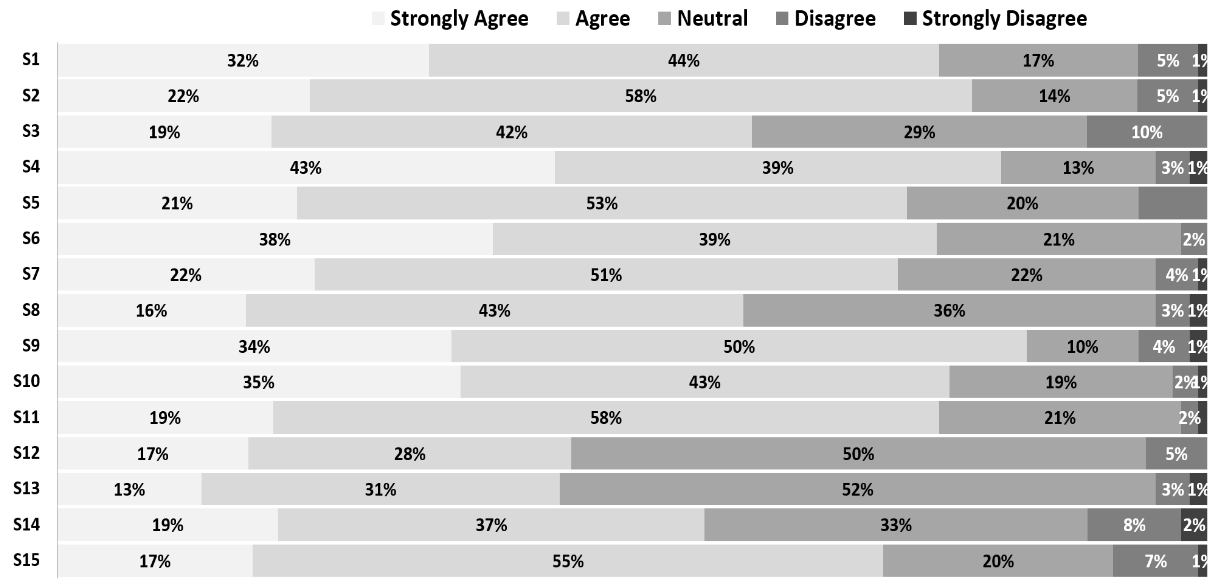
4.2.2 Descriptive statistics

The 5-point Likert scale questionnaire completed by 135 students from different courses consisted of 15 statement (see appendix I). The 15 statements are depicted as S1 to S15, with the responses to these statements being either ‘strongly agree’, ‘agree’, ‘neutral’, ‘disagree’ and ‘strongly disagree’. The frequency distribution of the responses from the students are shown in **Table 4-4**. The total responses to the 15 statements ranged from 132 to 135 which implies that among the 135 respondents, some respondents (3, 2 or 1) chose not to respond to some statements. Statements S2, S6 and S12, in particular, had 3 less responses whilst S1 and S11 had 2 less responses and S3, S4, S5, S7, S8 and S9 had 1 less response. Statements S2 and S6 were meant to assess the level of technical support received and the confidence that students had in using the VLE, which arguably are related (Parsons, 2017) and might explain the 3 less responses observed.

Table 4-4: Frequency distribution of responses to the 15 statements

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Number of Respondents
S1	43	59	23	7	1	133
S2	29	76	19	7	1	132
S3	25	56	39	14	0	134
S4	58	52	18	4	2	134
S5	28	71	27	8	0	134
S6	50	51	28	3	0	132
S7	30	68	30	5	1	134
S8	22	58	48	4	2	134
S9	46	67	13	6	2	134
S10	47	57	26	3	1	134
S11	25	77	28	2	1	133
S12	22	37	66	7	0	132
S13	17	42	70	4	2	135
S14	26	50	45	11	3	135
S15	23	74	27	10	1	135

A graphical representation of **Table 4-4** is depicted in **Figure 4-1** with the colour codes from light grey (strongly agree) to dark grey (strongly disagree).



Note: The lightest grey and the darkest grey areas represent the "Strongly Agree" and "Strongly Disagree" answers to statements. The areas between represent the different extents of agreement with the statements

Figure 4-1: Graphical depiction of responses to the 15 statements.

From **Figure 4-1**, it is evident that the largest area is the light grey portion which captures the 'agree' statements. The highest proportion of student agreement is to statement S9 (the need of online learning system) which shows the integral role that the VLE plays in the students' learning process. However, the need for training and support to be offered to students on the use of the VLE is also evident in the responses obtained for statement S3 (user-friendly and accessibility of the VLE with minimal training). The availability of training and technical support has a significant influence on the user experiences of VLE (Parsons, 2017). The student's user experience of the VLE has also been affected by the system's downtime and related technical issues as depicted in responses to statement S12 (system downtime) and S13 (technical issues). The challenges of IT infrastructure, including internet connectivity and system downtime, have been identified observed in several studies in both developed and developing countries (Asampana et al., 2017; Jackson and Fearon, 2014; Zapantis and Maniscalco-Feichtl, 2008).

The general agreement to the different aspects of the VLE is visible when the median and mode are computed as shown in **Table 4-5**. This confirms the colour-code representation depicted in **Figure 4-1** as the mode of 'agree' to statements is the highest, followed by the 'neutral' and 'strongly agree' to statements which have the same median. For the median, the 'neutral' item is the highest. The median for 'agree' to statements, however, is not available as there were no repeated figures for this item. The 'neutral' to statements was presented to respondents as 'neither agree nor disagree'.

Table 4-5: The median and mode for each of the items

Item	Median	Mode
Strongly Agree	25	28
Agree	N/A	58
Neutral	27	28
Disagree	7	6
Strongly Disagree	1	1

With mode for strongly agree and agree comprising the highest of the observation, an inference can be made from this observation that there is a general consensus among students regarding the usability and effectiveness of the VLE (i.e. Moodle) in enhancing their learning experiences (Boulton et al., 2018; JISC, 2016). The general aspects agreed to relate to the simplicity, clarity and user-friendliness of the VLE and also whether the VLE made the students' learning process easier. These student user aspects have been investigated in other studies (Lineses and Aguilar, 2019; Love and Fry, 2006; Robinson et al., 2017; Ogange et al., 2018) and identified as significant in making the VLE effective for students. In order to obtain some statistical generalisations and a more detailed understanding of the aspects of the VLE, inferential statistical analysis is needed. The inferential statistical analysis results are presented next.

4.2.3 Inferential analysis

A nonparametric test is used in the inferential analysis so as to test the distribution of data in order to observe if statistical errors have contributed to the obtained results through considering individual rather than aggregated answers. The chosen test is nonparametric because Likert scales provide ordinal, not interval data (Bishop and Herron, 2015). Moreover, the data collected is concerned with one group of students since no distinction has been made between students in terms of their courses, levels, gender or nationality. In this respect, there is no assumption regarding the distribution of the data (i.e. data not normally distributed) (Bhardwaj, 2017). A nonparametric test suitable for such data is the Chi-Square test (Bhardwaj, 2017; Rasmussen, 1986). The use of parametric tests on such data that is not normally distributed raises the risk of yielding meaningless results. Thus, the use of the Chi-Square test on the nonparametric data set obtained from the 135 students was appropriate for this study.

The chi-square test was conducted using the statistical software, SPSS, with the confidence interval chosen at 95% and thus, the significance level of 5%, after setting up the data in Microsoft Excel. The use of SPSS enhanced the data analysis process, making it easier to perform and also present the results in charts. In applying the chi-square test, the hypothesis being tested is:

H_1: *There is (student) evidence that PAAET's VLE/LMS is adequate (in terms of functionality, availability, user friendliness, collaborative, aesthetics, simplicity, security, privacy) to support the learning process.*

H_0: *There is **no** (student) evidence that PAAET's VLE/LMS is adequate (in terms of functionality, availability, user friendliness, collaborative, aesthetics, simplicity, security, privacy) to support the learning process.*

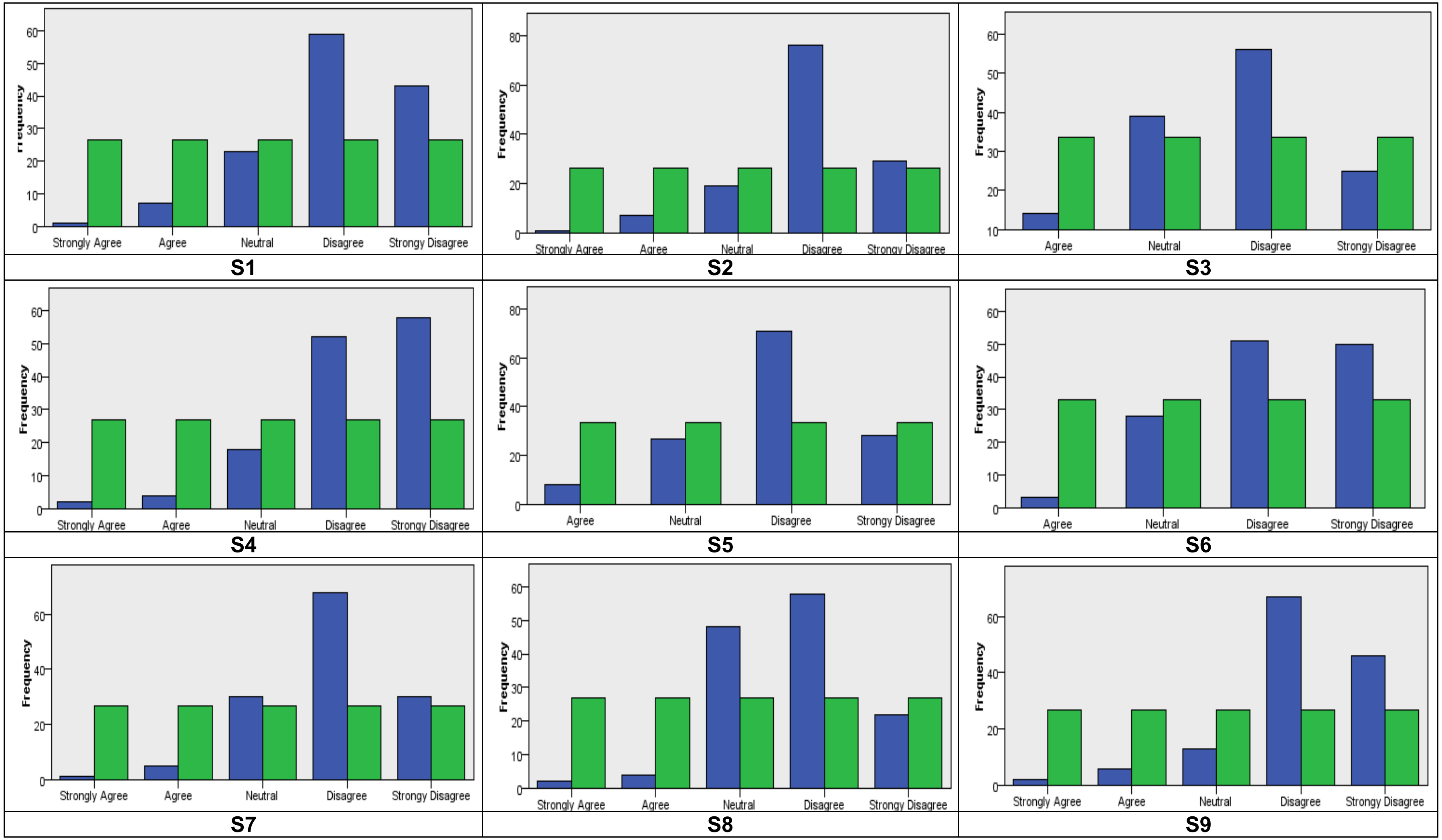
The results of the chi-square test are shown in **Table 4-6**. In all cases, the null hypothesis that responses to the statements occur with equal probabilities is rejected. Equivalently, this means that the alternative hypothesis (that responses do not occur with equal probabilities) should be accepted.

Table 4-6: The Chi-Square test results. All the item generated the decision to reject the null hypothesis

	Null Hypothesis	Test	Decision
S1	The categories of S1 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S2	The categories of S2 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S3	The categories of S3 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S4	The categories of S4 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S5	The categories of S5 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S6	The categories of S6 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S7	The categories of S7 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S8	The categories of S8 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S9	The categories of S9 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S10	The categories of S10 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S11	The categories of S11 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S12	The categories of S12 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S13	The categories of S13 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S14	The categories of S14 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis
S15	The categories of S15 occur with equal probabilities	One-Sample Chi-Square Test	Reject the null hypothesis

As such, the null hypothesis that "*there is **no** (student) evidence that PAAET's VLE/LMS is adequate in terms of functionality, availability, user friendliness,* *collaborative, aesthetics, simplicity, security, privacy to support the learning process"* is rejected.

A graphical depiction of the differences between the hypothesised values (represented in green) and the observed values (represented in blue) for each statement is shown in **Figure 4-2**. The figure shows that observed values do not fit the expected values obtained in **Table 4-5**, and thus, results do not fit the null hypothesis.


Frequency
Strongly Agree
Agree
Neutral
Disagree
Strongy Disagree
S1
S2
S3
S4
S5
S6
S7
S8
S9

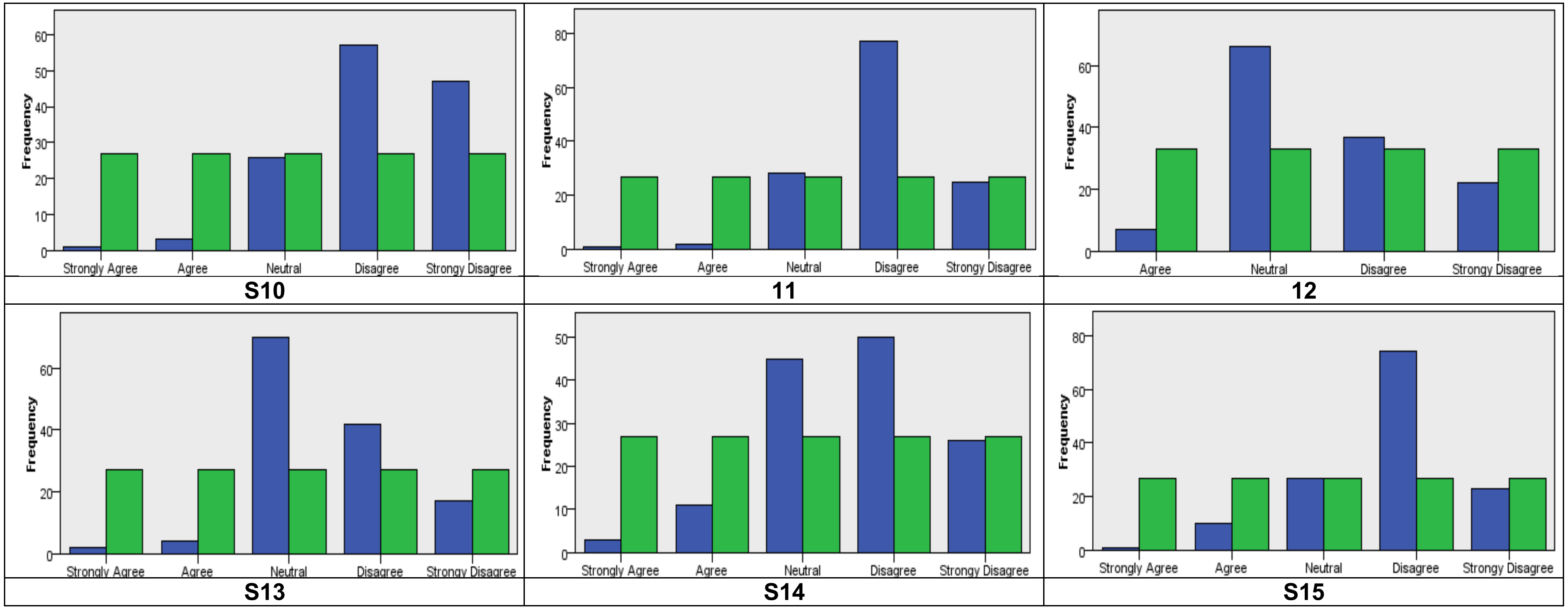


Figure 4-2: Differences between hypothesised values (green) and observed values (blue) for each statement

The results from the chi-square test, therefore, show that the responses from the students do not occur with equal probabilities. In other words, the observed results do not fit the null hypothesis, as observed values do not fit the expected values. Thus, there is a significant difference between the expected and observed values. This means that the hypothesis "*There is (student) evidence that PAAET's VLE/LMS is adequate in terms of functionality, availability, user friendliness, collaborative, aesthetics, simplicity, security, privacy, to support the learning process"* is accepted. Thus, student views of the adequacy of the VLE/LMS is positive.

Importantly, a favourable inference has been drawn from the statistical results about the students' views on the adequate of the VLE/LMS in terms of functionality, availability, user friendliness, collaborative, aesthetics, simplicity, security, privacy. However, these aspects are recognisably qualitative in nature, and thus, the use of a robust quantitative approach provides an acceptable estimation (Sun, 2012). The analysis of qualitative data from the interviews is presented next.

4.3 Qualitative Analysis

4.3.1 Approach to data analysis

The qualitative analysis of interview data from academic staff and system administrators (academic support staff) adopted a grounded theory approach. The review of the literature (see section 2.12) identified key institutional aspects that need to be taken into account when considering implementing LA in VLE. An understanding of these aspects could help to evaluate the readiness of an HEI's VLE to support LA implementation. As such, the questions to participants were meant to explore different aspects of the VLE which enabled perspectives on VLE readiness for LA to be obtained. This approach is necessary as it recognises that the implementation of LA requires as a first step, the presence of an effective and efficient VLE, that sets the necessary conditions for the full functionality of LA (Leitner et al., 2017).

4.3.2 Interview themes

Drawing on the literature review, some key aspects of LA implementation which could be linked to the interview themes are presented in **Table 4-7**. These have been identified from the literature as key considerations for LA implementation and thus become a reference point for analysing the interview data.

Table 4-7: Categories of LA implementation

Category	Description
CAT 1	Leadership
CAT 2	Vision
CAT 3	Culture
CAT 4	Ethics
CAT 5	Legal
CAT 6	Strategy
CAT 7	Resources

Thus, the categories formed the basic skeleton for the analysis of participants' perspectives regarding the VLE and LA implementation. This also provided an opportunity to explore emergent themes that do not fall within the 7 categories. The results from the analysis of interview data is discussed next. The key findings with respect to the themes are discussed.

4.3.3 Findings

The themes that emerged from the data analysis linked to the LA implementation categories shown in **Figure 4-3** and discussed next.

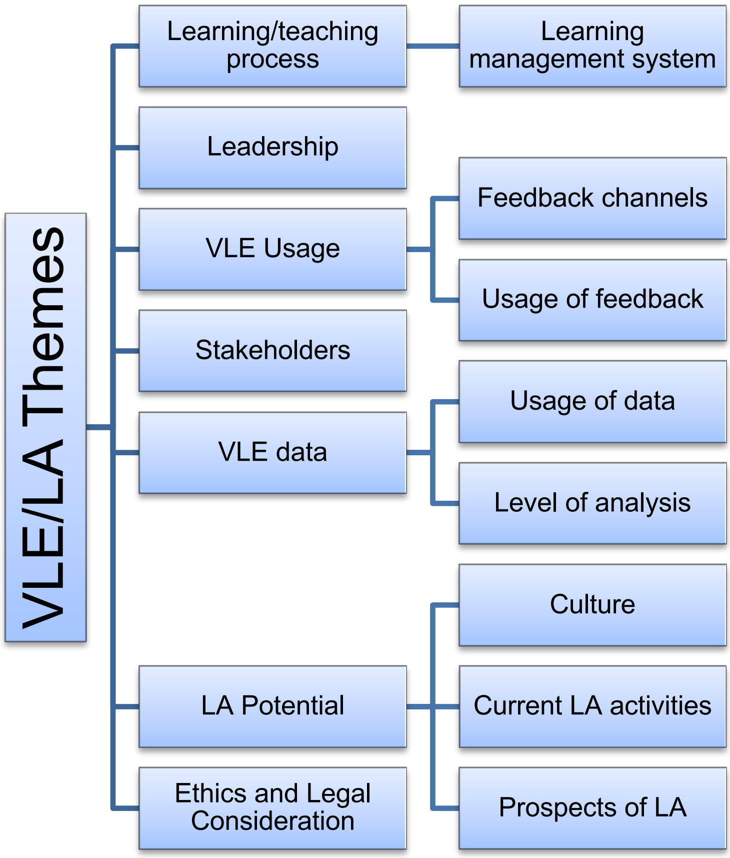


Figure 4-3: Interview themes

4.3.3.1 The learning/teaching process at the institution (CAT 7)

The learning process is mainly based on traditional classroom teaching for all modules. Additionally, some material is placed on Moodle, the learning management system used, and is accessed by students. There is no evidence of the use of advanced aspects of eLearning in the sense where students are involved in accessing and exchanging content, or in distant learning currently implemented. There are, however, prospects for future utilisation of the LMS to support eLearning.

The interviewees consent that Moodle provides a good learning management system for the tasks needed. Also, system administrators point out that Moodle provides good value and low operational cost compared to the other platforms (such as blackboard).

4.3.3.2 Individuals involved in using the VLE (CAT 3)

The recognition of key stakeholders and their needs of the VLE forms an important step to meeting expectations through making changes and improvements to the learning system (Dollinger et al., 2019; Greller and Drachsler, 2012; Hommel et al., 2019; Khalil and Ebner, 2015). This is also key as it helps reduce the resistance to change that could potentially arise if the stakeholder expectations are not met or their needs sufficiently communication. Essentially, learning is an interactive process. The interviewees identified the VLE users at the institution as students, academic and managerial staff involved in the learning services (see section 2.4).

4.3.3.3 The use of the VLE (CAT 2, CAT 6 & CAT 7)

The VLE at the institution is mainly used to send notifications, provide module descriptions, and post assignments. The system administration staff stated that Moodle is also used to increase the efficiency of the services provided to the parties involved in the educational process, which helps improve the quality of learning. In this respect, the VLE has changed the way the institution handles its teaching, learning and assessment by providing a means to structure, manage and deliver learning activities and contents (Boulton et al., 2018; JISC, 2016).

Further, in the attempt to improve the VLE usage, feedback is received from the key users. Any feedback regarding the use and content of the system is directed to the system administrators using the e-form program application. It is a software application made available for staff to send their thoughts and feedback in manner similar to sending a text email. According to the system administration interviewees, the feedback collected from the staff is then used in planning improvements.

4.3.3.4 Virtual Learning Environment Data and Analysis (CAT 2 & CAT 7)

The academic staff interviewees indicated that they receive basic information about the students on the course from the system (Moodle), which includes the course contents as set by the course leaders, the students on each module, student frequency of access to the system. This information is used as an input in planning teaching over the time of the course. For instance, if a module had low online access rate, this could be recognised by the lecturers and reported to the module leader.

With respect to the usage of the information on the VLE, the interviewees recognised some aspects of advanced data analysis being done on the information received, such as connecting low access to course material and students' performance which then triggers the need for change. Other information studied include assessment results, attendance, number of students, etc. which is used to plan for courses in the following term.

The system administration interviewees highlighted that the system per se does not provide advanced analysis tools. Only basic data and some statistics was presented in tables. The interviewees recognised that more features are required to conduct further analysis of the data provided by the system. In this respect, some descriptive and diagnostic level of data analysis is evident (Boyer and Bonnin, 2016) (see section 2.13) which is used to mainly improve course delivery.

4.3.3.5 Learning Analytics implementation potential (CAT 1, CAT 2, CAT 3, CAT 6 & CAT 7)

The interviewees highlight that LA has not been a primary concern of the institution. Nevertheless, there has been some movements towards understanding the potential of LA at the institution without any actual projects taking place. According to the system administration interviewees, there have been several committees formed at times to discuss and develop LA projects, but they have not been implemented. These committees have prepared reports of the situation of the institution and what needs to be done in order to achieve these projects. However, no hard implementation has been conducted. As such, the interviewees highlight that LA is still limited to forming specialised committees that prepare statistical schedules and programmes and provide information to decision makers.

This is evident from the academic staff interviewees who explained that they have not been made aware of any current or potential use of LA in the institution. Apart from forming committees to study the applicability of an LA project in the institution, there seems to be no concrete plans as yet to implement LA by the HEI.

In terms of prospects and benefits that LA could bring to the HEI, academic staff interviewees acknowledge that LA can help provide effective results that could improve teaching and learning. In particular, the interviewees highlight that a properly implemented LA project would provide a significant response to recurring issues as it would assist in developing solutions and also improving the quality of services provided by PAAET. The system administration interviewees also noted the potential benefits of successfully implementing LA with one interviewee commenting that:

> expanding and diversifying the departments of PAAET and its colleges. This has been done through the results provided by our current analyses and will be effective in the future if LA applications are conducted and expanded.

This highlights that basic descriptive and diagnostic data analysis has already been useful, thus, advanced levels of analysis would even be more beneficial in driving decision making. In this respect, interviewees explained that LA would have a prominent role in making important decisions where all organisational aspects of the institution are considered in light of LA and provide the basis for management to take informed intervention action as a result of the data analysis. Further, system administration interviewees expressed an awareness of several significant outcomes that LA could bring to the learning process as well as to the development of the institution as a whole. Some of the highlighted outcomes include: organisation of admission and registration process, improving decision making, developing comprehensive quality programmes, achieving competitive advantage, contributing to the academic development of the institution. These are all aspects that have been highlighted in the literature from a fully operational LA project (Arroway et al., 2016; Larrabee Sønderlund et al., 2019; Waheed et al., 2020).

4.3.3.6 Ethical and Legal Considerations (CAT 4 & CAT 5)

Section 2.11 highlighted that ethical and legal considerations in LA project implementation form an essential aspect that need to be taken into account. As such, questions about ethical and legal considerations were addressed to the system administration interviewees in managerial positions.

The interviewees revealed awareness of the need to address security concerns, which was better than privacy related issues. The interviewees explained that PAAET has an established security policy regarding data and associated information whereby only authorised personnel have access to analytics data. However, privacy considerations are not well-addressed as it wasn't made clear to the researcher how privacy is established/promoted with respect to the data collected by the institution. Also, there was no clear view on how legal issues related to the application of LA could be addressed if these arose.

4.3.3.7 Leadership/governance (CAT 1 & CAT 2)

With respect to leadership commitment, the analysis of the interviews revealed that there is no obvious commitment of using LA for decision making and that senior management has little involvement in LA. As such, there is no clear indication of the strategic direction of LA implementation. As for the organisational vision on LA, the analysis revealed that only basic information is collected, although certain awareness of advanced uses exist that have not been practically considered. There is a feedback system implemented for improvement of teaching but is still limited. For the acceptance culture, it was shown that students and staff are familiar with the VLE in use and they are willing to use advanced feature if these existed. As such, the possible resistance to change is envisaged to be minimal. However, the HEI has not yet put a concrete plan for LA project implementation.

Table 4-8 summarises the above discussion with respect to the LA categories in order to give an overall overview of the findings from the qualitative data analysis.

Table 4-8: Overview of qualitative data analysis results

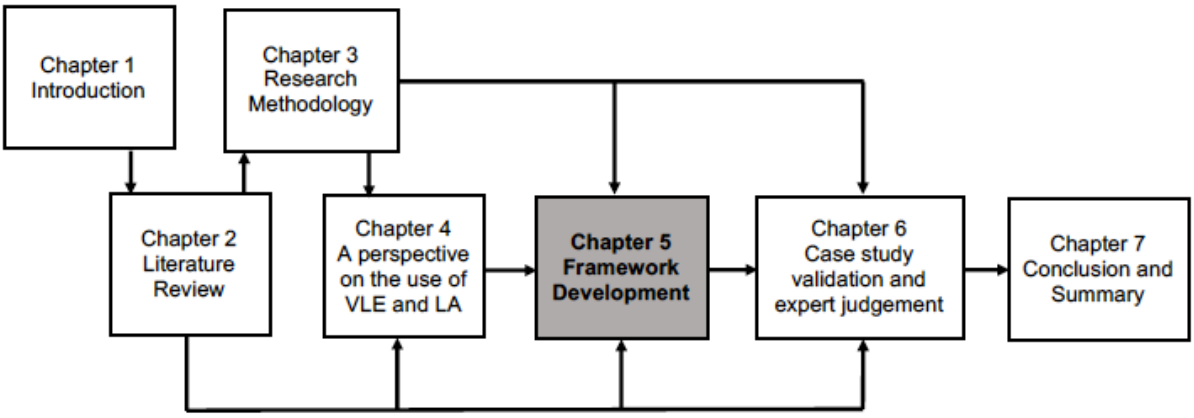
Code	Category	Description
CAT 1	Leadership	• No obvious commitment of using LA for decision making • Senior management shows little involvement in LA • No clear indication of leadership prospects
CAT 2	Vision	• Basic information collected • Awareness of advanced uses but not practically undertaken • Feedback system implemented for improvement but still limited
CAT 3	Acceptance	• Students and staff are familiar with the VLE in use • Willingness to use advanced feature if existed • No LA projects have been implemented
CAT 4	Ethics	• Ethical considerations have not been addressed • Security of data seems to be acknowledged but not implemented
CAT 5	Legal	• No evidence of any policies considered to deal with arising legal issues of LA projects, including security and privacy
CAT 6	Strategy	• Committees have been formed to discuss LA implementation, but no implementation has been undertaken
CAT 7	Resources	• No evidence of advanced e-learning use • Dependence on Moodle due to value and cost effectiveness • VLE has relatively limited use

4.4 Summary

The aim of this chapter was to discuss the findings from the field study phase of this research. The field study stage adopted a case study strategy in order to gain an high-level perspective on the utilisation of the VLE/LMS and the prospects for LA implementation from key stakeholders. The HEI case study used is the Public Authority for Applied Education and Training (PAAET) of Kuwait, one of the largest HEIs in the Middle East with students from all over the world. The perspective of students was obtained via online surveys which provided the quantitative data for analysis with results discussed in section 4.2. The perspective of academic staff and system administrators (academic support staff) was obtained via semi-structured interviews which provided qualitative data for analysis with results discussed in section 4.3.

In general, the student perspective regarding the VLE usage and its effectiveness are positive. Some aspects related to the need for training and technical support in order to fully utilise the learning management system were raised. The analysis of qualitative data revealed the usage of the VLE for mainly course content delivery, providing access to learning materials for students. Some level of descriptive and diagnostic data analysis is implemented though no advanced analytics tools have been implemented. Further, different aspects that show commitment to LA project implementation are lacking reflected by the general lack of leadership, strategy, vision, infrastructure and resources. This highlights that for the PAAET to implement LA, significant institutional capacity has to be developed. However, there is evidence that user acceptance of changes is high which is good grounds for instituting change. The next chapter builds on the understanding gained from the field study and the systematic review of the literature in developing a LA maturity assessment framework.

5 FRAMEWORK DEVELOPMENT



5.0 Introduction

This chapter presents the LA maturity assessment framework that has been developed based on the extensive and systematic review of the literature (chapter 2) and the findings from the field study (chapter 4). A multi-phases research methodology, from a multi-theoretical perspective (chapter 3) was adopted in developing this LA maturity assessment framework. In the multi-phases methodological approach (see section 3.4) this research stage is depicted as phases 3, 4 and 5. The LA maturity assessment framework ('the framework') comprises three interrelated components: maturity level model ('the model'), the performance measurement tools ('the tools') and the road map recommendation ('the road map'). These are interrelated components as the tools help to position a HEI on the maturity level in the model which then informs how progression can be made on the road map. The next section presents the developed maturity model.

5.1 Maturity level model of using LA in VLE

5.1.1 Overview of the maturity level model

The development of the maturity model of using LA in VLE provides a valuable reference for positioning the implementation of LA in HEI. In understanding, interpretation and application of the model, it's important to recognise that institutions are non-static and that the different levels in the model can be perceived as more of a continuum. In this regard, the more advanced levels of the model cannot be obtained without the basic levels having been attained first. The developed maturity model consists of five levels as shown in **Figure 5-1**. The model has been designed graphically with three elements, these are: the left element shows the title of each level, the centre shows the different functions in each level and finally the right element shows the meaning of the expected output of each level. The following are the five maturity levels:

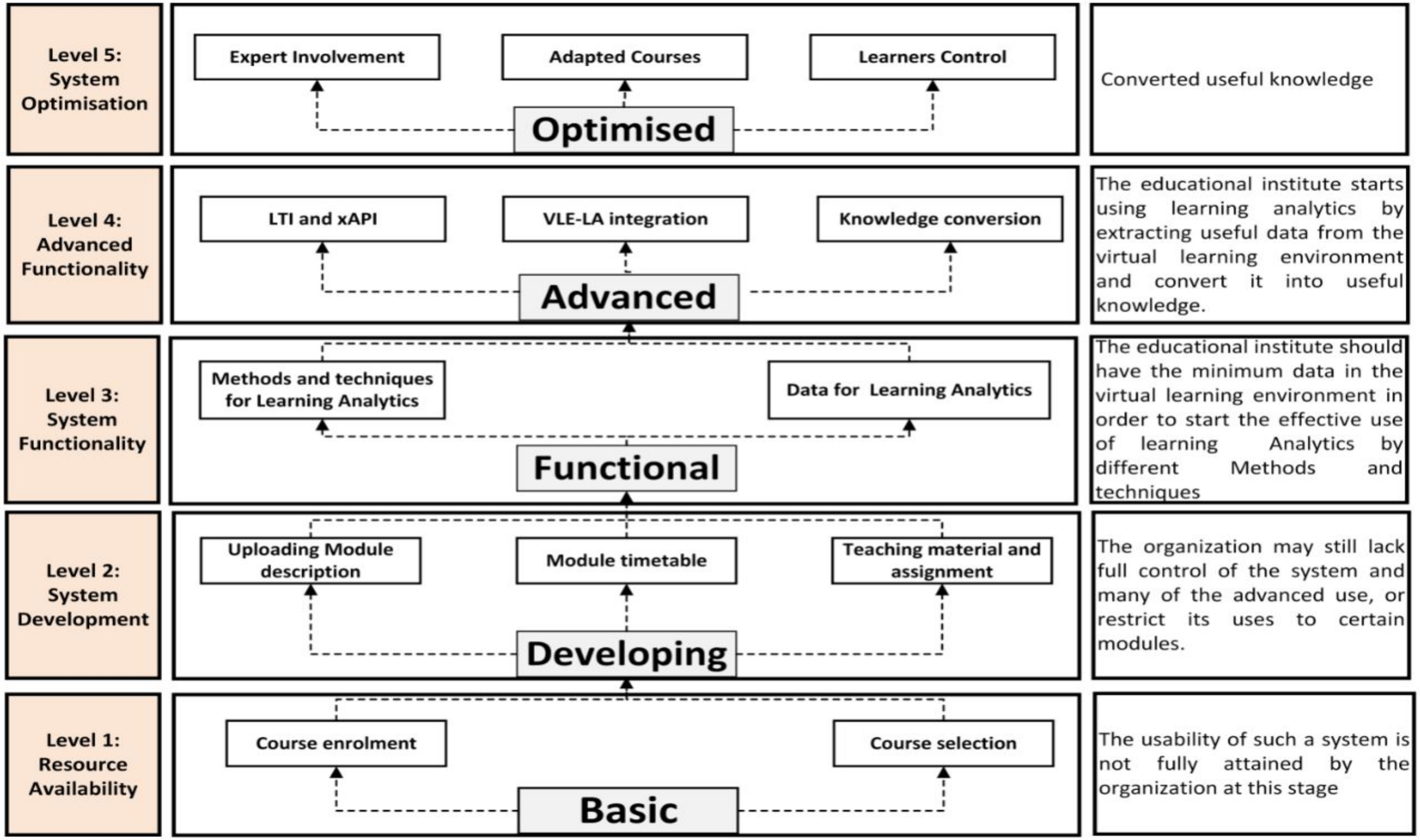
- Level 1 – Resource availability: the technical infrastructure lacks efficiency and comprehensiveness at this level. The academic and support staff as well as students have the typical access to the VLE facilities. The VLE has limited data such as course handbook, course learning materials and assessment details.

- Level 2 – System development: the technical infrastructure for the VLE is developing and getting more efficient. At this stage, the system would be functioning but not to full capacity. In particular, whilst all digital content could be offered online at this level, not all users would have access to the content as its ability to handle multiple users is still limited.

- Level 3 – System functionality: the scope of the VLE becomes wider in terms of data capture and accessibility to all users. The data availability (e.g. on demographic, academic, learning activity, educational context) and the existence of standard implementation procedures support LA. LA is implemented to extract useful data from the fully functional VLE. As the VLE is more advanced, multimedia use for course delivery becomes more frequent. The Integration of LA into the VLE is facilitated by Application Program Interface (API) and Learning Tools Interoperability (LTI) (Ochoa and Ternier, 2017).

- Level 4 – Advanced functionality: the use of LA in the HEI increases; extracting useful data from the VLE and converting it into useful knowledge to monitor learning quality and process performance. The utilisation of learning analytics is towards predictive analysis.

- Level 5 - System optimization: further system optimisation is considered, including automated discussion forums, adaptive courses and expert involvement. Advanced learning analytics techniques are employed to support predictive and prescriptive analysis of data from the fully functional VLE. More integration of learning analytics into the organisational improvement processes occurs at this stage. The maturity model is graphically represented in **Figure 5-1**.



LTI - Learning Tools Interoperability (LTI); xAPI – Experience Application Program Interface (API)

Figure 5-1: Maturity model of learning analytics in virtual learning environment

5.1.2 Maturity model and user interactivity in the learning process.

The following sub-sections present in some details each of the five maturity levels. The different learning process are presented as well as the interactions of the main user groups (academic staff, academic support staff and students). This is important as the maturity model has taken into consideration user interactivity.

5.1.2.1 Level 1: Basic – resource availability

The basic level is for making sure the availability of the basic VLE resources in terms of hardware and software. In addition, to have the basic functionality of the VLE. The basic level reflects a phase in which the VLE supports limited functionality; lacking efficiency and comprehension. In respect to the utilisation of the system by the three main user groups, this includes:-

- Academic staff use the VLE to support their planning, teaching and review activities. This is done by accessing basic information on the current academic programmes and courses as well as feedback obtained from students. This is done to enhance current academic curriculums and assist in the development of new ones. Besides, the academic staff uses VLE to support their course delivery by providing essential course content such as module outlines and teaching materials.
- Academic support staff uses VLE at the basic maturity level to support student registrations, which include partial demographics data, contact details, different course handbooks and modules descriptions. Also, they make sure that timetables on space locations are available in VLE. They interact with the students via basic email using the functions of the VLE.
- The students use VLE to access and download the course and modules information such as handbooks, timetable and teaching materials. The VLE is becoming its basic platform to communicate with academic staff and academic

support staff. Therefore, this maturity level supports the basic learning process of the students.

5.1.2.2 Level 2: Developing – system development

The developing level is for enhancing the system's development in order to improve its functionality. At this level, the VLE should have improved functionality with a supportive technical infrastructure. The improved technical infrastructure helps support online digital content and data capture in the VLE. This level is reflected by having a stable course management system, such as Moodle or Blackboard. The VLE utilisation by the main users could include:-

- Academic staff has increased accessible tools and functionality of the VLE to support the development of the digital contents of the courses. However, some existing functionality of the system would still not been utilised fully by the academic staff. Nonetheless, academic staff has more options to perform operations, like communicating with students, marking students' assessments and feedback as well as providing course-related activities.
- Academic support staff is supporting the academic staff in uploading the course information in the VLE. This includes course handbook, module description, teaching material, timetables and assignments. In addition, these support students to access the course material and address any student problems. In addition, academic support staff assists students on how to upload assignments, addressing any problems in the process and making these available to the academic staff for marking. Finally, they make the module's feedback forms available online to the students.
- The students will be able to do course selection and download the course content. In addition, students have access to all relevant course information and upload their assignments into the VLE. The students are also able to

provide online feedback on each module. At this level, the students have sufficient connections with academic staff and academic support staff.

5.1.2.3 Level 3: Functional – system functionality

The functional level aims to make full use of the different system functionalities. At this level, the maturity of a HEI's VLE will have become more apparent in many aspects with an increase in data availability. There is an increased use of multimedia in course delivery and the progress to integrate learning analytics into the VLE. The main user groups' interactions with the VLE include:-

- Academic staff – all the information on the courses and their modules are available online via the VLE. Academic staff makes full use of the functionalities available in the VLE. In addition, all the academic marking and feedback to the students are also done via the VLE.
- Academic support staff – they support the academic staff to make all the information on the courses and their modules available online via the VLE. Beyond this, they collaborate with academic staff to make data available for learning analytics. Some descriptive and diagnostic data analyses could be performed to better understand student performance (i.e. to understand what happened and why it happened).
- Students have full access to all the academic information via the VLE. Courses become more adaptable to students and more flexible in delivering their goals. The scope of the VLE becomes wider in terms of supporting students, for instance, in initiating student-academic staff meetings/engagement.

Data at this level is more abundant and readily available in the HEIs via VLE. The data types are demographic, academic, learning activity and educational context nature (see section 2.8).

5.1.2.4 Level 4: Advanced – advanced functionality

The advanced level is for utilising the fully functioning VLE in order to start LA implementation. At this level, the educational institution starts to make effective use of LA by extracting useful data from its VLE and converting the data into useful knowledge. LA is integrated into the HEI's VLE using educational technologies of Application Program Interface (API) and Learning Tools Interoperability (LTI). The API gathers data in a specific format about the students and allows tracking of the learning activities from any compatible system. An API, also xAPI for experience API, which is a learning-specific API, allows an institution to collect student interactions with the learning management system (LMS) and transfer the records of these interactions in a common format to supported applications. APIs may be native to the LMS or provided as a plug-in. The LTI provides a framework for integrating an LMS with LA for enabling various learning tools to communicate with one another and share information with the institution's LMS. The interaction at this level of each user group could include:

- The academic staff can observe students' performance while the course is running. Accordingly, they can adapt the course or modify content. This also includes identifying students or student groups facing difficulties earlier, interfering in course delivery by assisting, and a drawing conclusion on the course outcomes. Thus, the engagement is towards predictive analysis to better support the student learning process.
- The academic support staff could also utilise data to better understand the courses and develop necessary policies that could help to maintain better student retention rates and other performance criteria for the entire institution.
- The students will benefit from a course adapted to their levels of performance, extended support tailored to their needs and a wider range of tools that facilitate and improve their learning experience.

5.1.2.5 Level 5: Optimised – system optimisation

The optimised level is for advancing the LA implementation process through optimising the system. At this stage, the VLE has already become mature, thus, further activities performed are tweaks and optimisation of processes. A HEI continues at this level the automation of many processes that have remained manual paving its way to becoming a mature VLE. The LA in VLE becomes increasingly integrated into the organisational improvement processes. Some interaction of each user group in this mature level include the following:

- Academic staff: discussion forums are more prescriptive analysis results-driven; reflecting more students control over subjects. Courses become adaptive based on past runs and require little interference from instructors. Assessments become increasingly self-generated from the system; more students tailored to identified areas of weaknesses. As the assessment is system generated, their occurrence or frequency is not limited.
- Academic support staff: the stage demonstrates a sense of commitment to quality. There is increased expert involvement to ensure the continued integrity of the education system. The expert involvement could be in course design and development based on prescriptive analysis of data. The VLE is functionally operating to its full capacity; quality is driven and distinguished by more expert involvement in many of its aspects. It effectively contributes to organisational improvement processes.
- Students at this level of the VLE maturity can take more control of their learning. Provided with more information on their progress and performance at an early stage, the students will be able to make informed decisions about their learning and appreciate the learning experience they achieve.

The maturity levels of LA in VLE in HEI can be connected to the learning process and main user interactivity as shown in **Table 5-1**. The learning process comprises of review and planning, curriculum development and course delivery (Sclater et al., 2016; Viberg et al., 2018) (see section 2.4). **Table 5-1** depicts the interaction of the key users in the three main learning processes at each different level of maturity. This helps give a more comprehensive picture that also shows that LA is focussed on learners and their learning environment (Long and Siemens, 2011). For example, at level 1, academic support staff will have basic data such as demographic data and contact details in the review and planning process. However, as an HEI progresses to level 4, more data types are available with data analytics becoming possible. The next section discusses performance measurement tools.

Table 5-1: Maturity levels, learning process and user group interaction

	Review and Planning		Curriculum Development		Course Delivery		
	Academic support staff perspective	**Academic staff perspective**	**Academic support staff perspective**	**Academic staff perspective**	**Academic support staff perspective**	**Academic staff perspective**	**Student perspective**
Level 5	Data analytics is the new norm	Knowledge accumulated to predict course plans	Experts involved in the design and development of the course	Course evolves based on previous runs	Knowledge management used to drive improvement in course delivery	Assessments are mainly self-designed based on the course run with little involvement from instructors	VLE fully functional and quality driven
Level 4	Data analytics possible	Clear view of course from data results	Partial results from analytics applied in development	Material customised to learners	Courses tailored according to acquired knowledge	Course more adaptive and learning is more effective	Course is more self-paced and content more suitable
Level 3	Data needed for course management are available	Course planning possible based on collected data	Wider VLE scope in terms of functionality and reaching learners	Courses more adaptable to learners and more flexible	Ability to manage communication solely over VLE	Use of multimedia becomes more common	Course mostly available on VLE with little need for physical meeting
Level 2	Learner-instructor interaction footprint more evident	Basic course authoring tools available	Ability to maintain and develop the system	Ability to interact with learners	Course management available	Lecture notes available with limited to no multimedia content	Ability to access material but with need for physical meeting with instructors
Level 1	Partial demographic data and contact details	Access current academic programmes and student feedback	Basic access to learning interaction	Define new courses and modules	Make available some Course details in VLE*	Putting module description, Teaching materials in VLE	Access some course and modules information

*VLE – Virtual learning environment

5.2 Performance measurement tools for using LA in VLE

5.2.1 Overview of the performance measurement tools

The development of the performance measurement tool ('the tools') is phase 4 in the multi-phases research methodology. The tools are used as an instrument to indicate as to the level of maturity of LA application within the VLE at HEI. This tool has been developed based on a balanced scorecard approach (Brown, 2007) to measure four perspectives, these are:

- Process.
- Infrastructure.
- Data.
- Human resource skills that are associated with the VLE.

These four areas have been identified as key to developing the institutional capacity for LA (see section 2.12). As highlighted in section 2.12, institutional capacity has to be developed in these four aspects for successful implementation of LA. These four components were identified from the extensive literature review and also highlighted in the field study (see section 4.3.3).

Thus, the performance measurement tool is made up of key questions for each of the four perspectives that should be addressed for an HEI to evaluate the level of LA maturity. The questions essentially act as a checklist. This is a balanced performance measurement tool which means each perspective has got the same number of the questions. It has been designed with 10 questions for each perspective.

The responses to each question, there are scores from 1 to 5 and the cumulative weighting of these helps to identify the maturity level position of an HEI as Level 1 to Level 5 accordingly. The response range of questions from each area captured as 1 to 5, therefore, corresponds to the 5 maturity levels identified in the model (basic, developing, functional, advanced and optimised). In total, 10 questions have been developed for each area which could be used to map the position of an HEI on each area which then feeds into the institutional weighting for all the four areas to identify the maturity level. **Figure 5-2** shows the performance measurement process. An example of the mapping result from the performance measurement process is shown in **Figure 5-3**. The example in **Figure 5-3** represents an ideal situation where an HEI is compared to a perfect situation of an optimised maturity level 5 score. Thus, the ideal would be that the scores for each question in the component would be at 5. However, an HEI comparison with a good practice or higher level scored HEI would be realistic. The next sections discuss in detail the questions and the associated rationale.

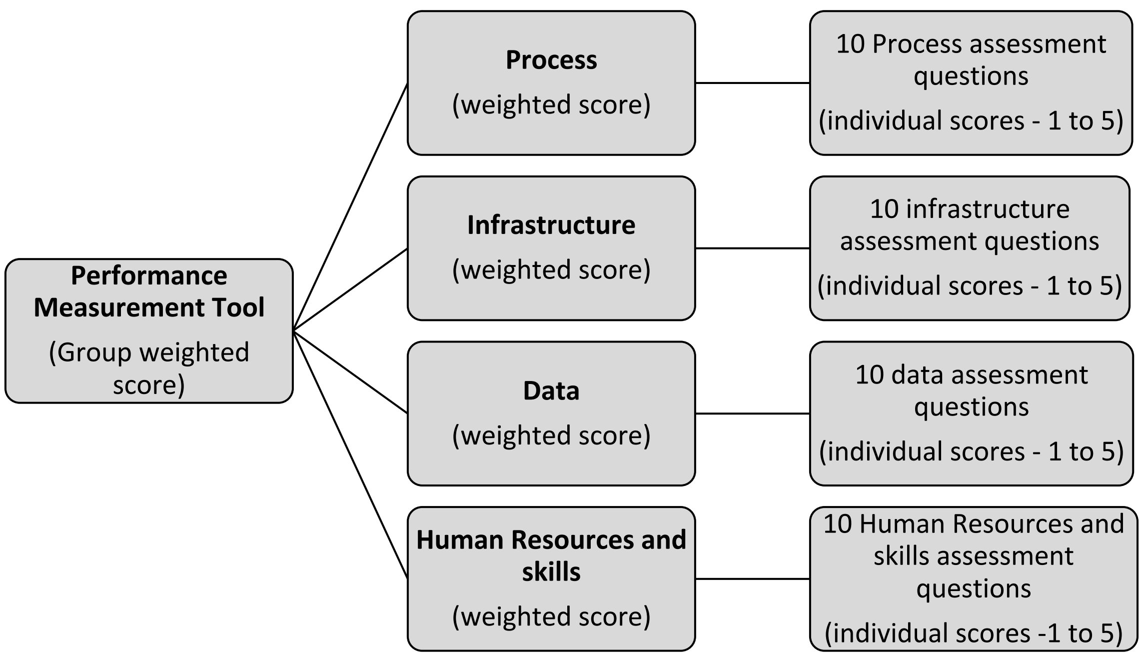


Figure 5-2: Performance measurement assessment process

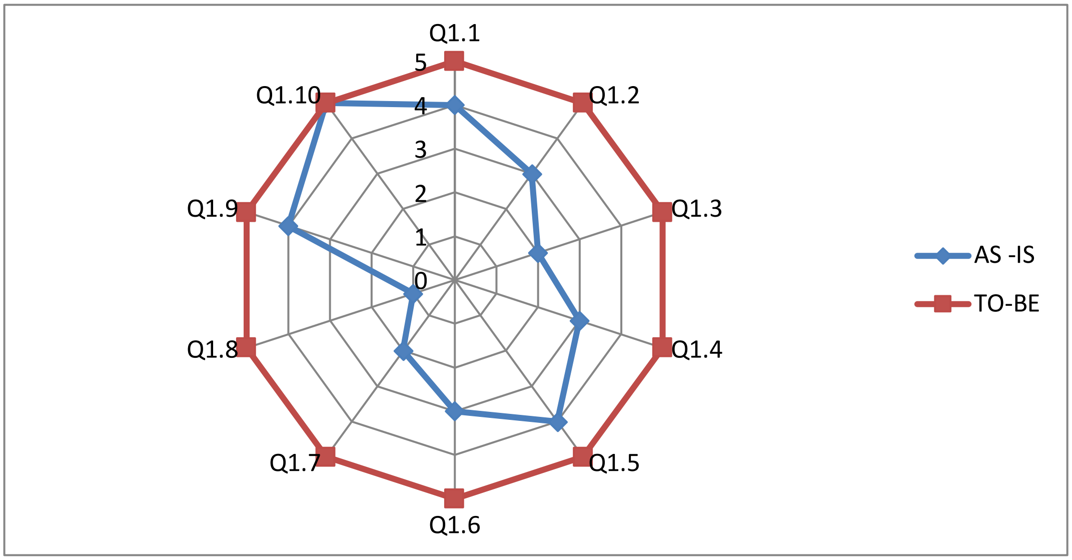


Figure 5-3: Example of response for a process perspective

5.2.2 Four main perspectives

The assessment of LA maturity is derived based on the 10 key questions developed for each of the four perspectives, process, infrastructure, data and human resources. These key questions and their relevance to the assessment process of LA maturity are discussed below.

5.2.2.1 Process

The processes that an HEI puts in place has a significant contribution to the success of LA implementation. To achieve full LA functionality, the processes and practices need to be embedded or integrated into the culture of the institution and be used effectively by the key stakeholders (Norris and Baer, 2013).

The questions on process relate to the identification, planning, designing and implementation of a new degree programme; control, management and maintenance of the learning process; existence and integration of process to capture students’ behaviour, satisfaction and performance; benchmarking of performance; and monitoring and control of performance. The aim in this respect is to evaluate the processes that contribute to the learning process, including those that promote quality. **Figure 5-4** provides the formulated key questions for the process perspective which are detailed in Appendix B.1. As shown in **Figure 5-4**, there are 10 sets of questions numbered 1.1 to 1.10. Each of the questions has responses of 1 to 5 as depicted in Appendix B.1. The questions were derived after an extensive review of the literature, the understanding gained from the field study, the wider consultation with supervisors and the refinement done after expert judgments. The presentation of the other three components follows this format.

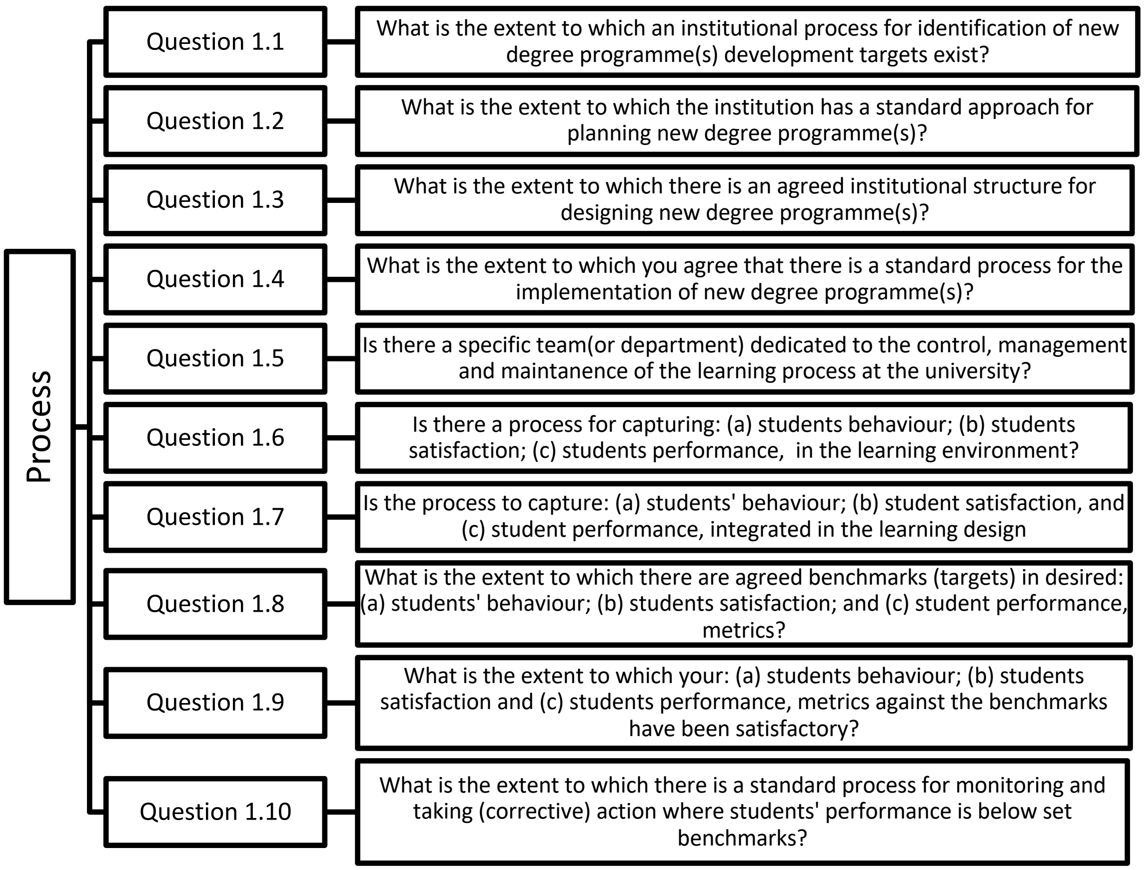


Figure 5-4: Process component assessment questions

5.2.2.2 Infrastructure

The existence of adequate infrastructure to support the implementation of LA is key (Yanosky and Arroway, 2015). The infrastructure that an HEI has should support the different aspects of LA applications. Fundamental to this aspect is the existence of a functional VLE with analytics tools and software that can store, manage, collect, analyse and interact with users (Norris and Baer, 2013). Thus, the tools and applications that enable easy data capture and data availability should exist.

The evaluative questions in this component related to the existence of the VLE that is functional, accessible, supported and monitored. In addition, the existence of analytics tools and software, including their implementation, integration and monitoring, are evaluated. The key issue is that the existing structure should enable users to access data that would improve decision making. The implementation of LA software and its integration into the VLE is a step towards a higher maturity level (Sclater, 2017; Yanosky and Arroway, 2015). **Figure 5-5** provides the infrastructure assessment questions for LA readiness and implementation progress, which are detailed in Appendix B.2.

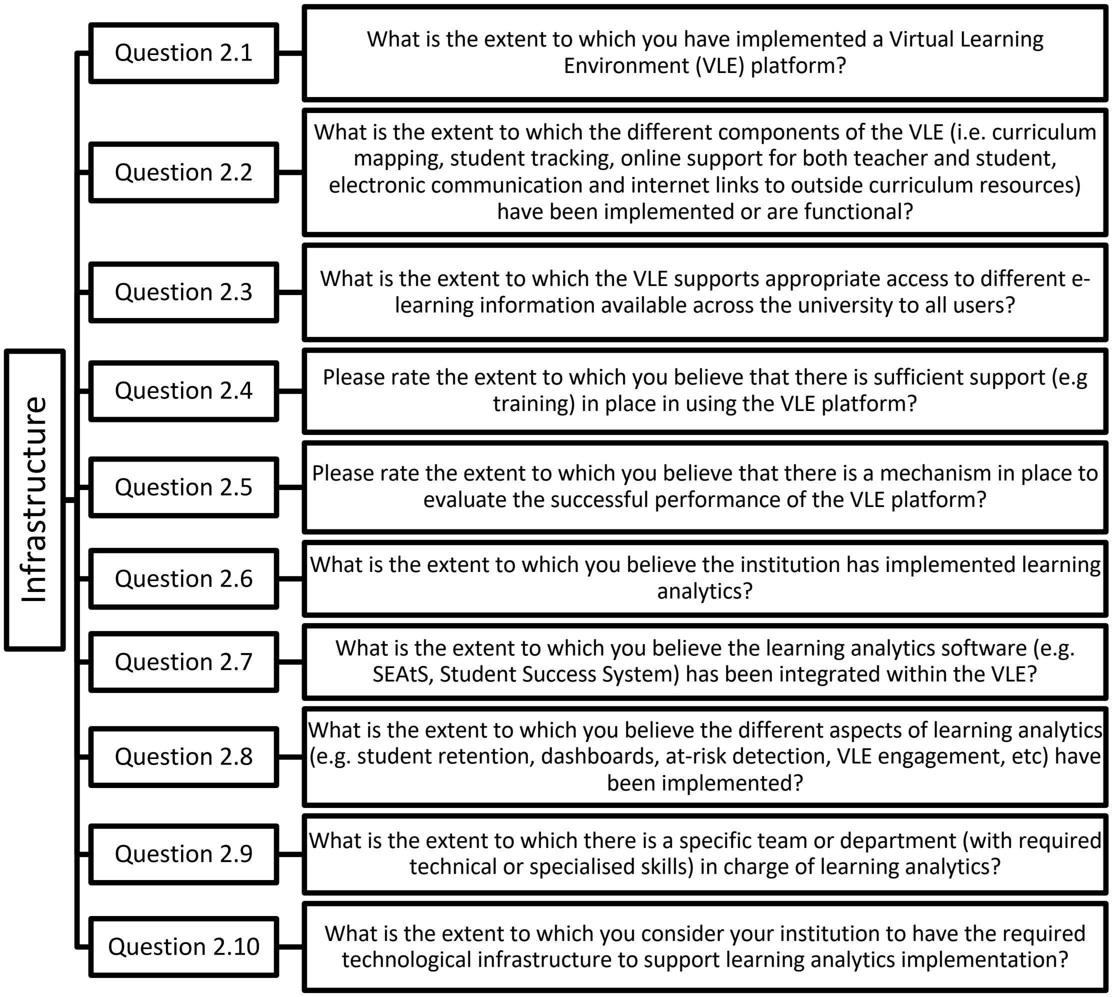


Figure 5-5: Infrastructure component assessment questions

5.2.2.3 Data

This aspect relates to data collection, access and usage and also data efficacy (Alexander et al., 2019; Arroway et al., 2016). The data efficacy is meant to enhance the data quality, its rightness for usage and analysability. These are significant aspects of data that should support LA implementation.

The data assessment questions revolve around the availability of data (e.g. on student experience) and the analysis of this data; the existence of data analysis software and its utilisation, and the purpose and nature of this analysis (e.g. for student retention, student engagement). The assessment is also aimed at evaluating the monitoring mechanisms, training availability and ethical consideration regarding data usage. **Figure 5-6** shows the data assessment questions with the detailed questions given in Appendix B.4.

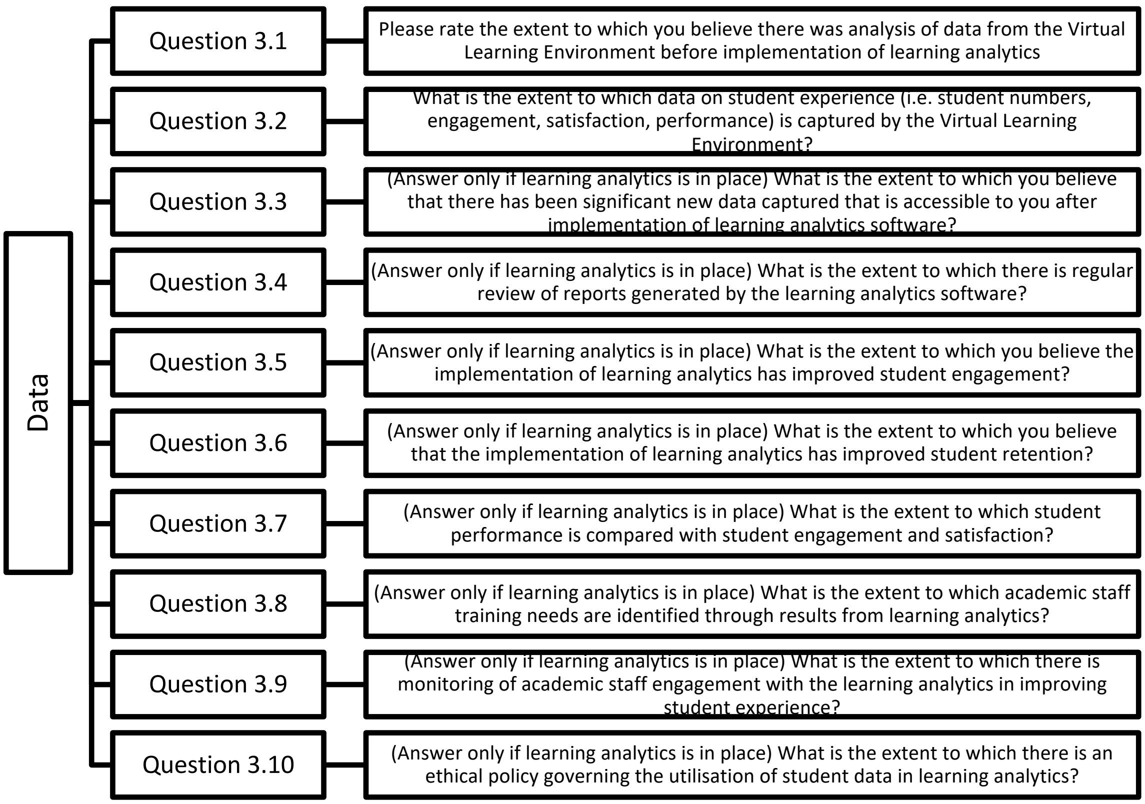


Figure 5-6: Data component assessment questions

5.2.2.4 Human resource and skills

Human resources and skills are integral to the successful implementation of LA in an HEI (Shacklock, 2016). As such, an HEI must invest in human resource and skills development so that an appropriate level of human resources and expertise is available, not only to undertake the analysis of the data from the VLE/LMS but also for the provision of technical support. Technical support, for instance, through training is needed to improve user confidence and acceptance (Asampana et al., 2017; Jackson and Fearon, 2014; Nawroth et al., 2015).

Thus, the assessment questions revolve around the availability of technical staff with an appropriate level of expertise to offer training and support; the investment in technical skills development; communication process, and review and monitoring, and the overall promotion of a technology supportive culture. **Figure 5-7** outlines the human resources and skills assessment questions and Appendix B.4 gives the detailed questions.

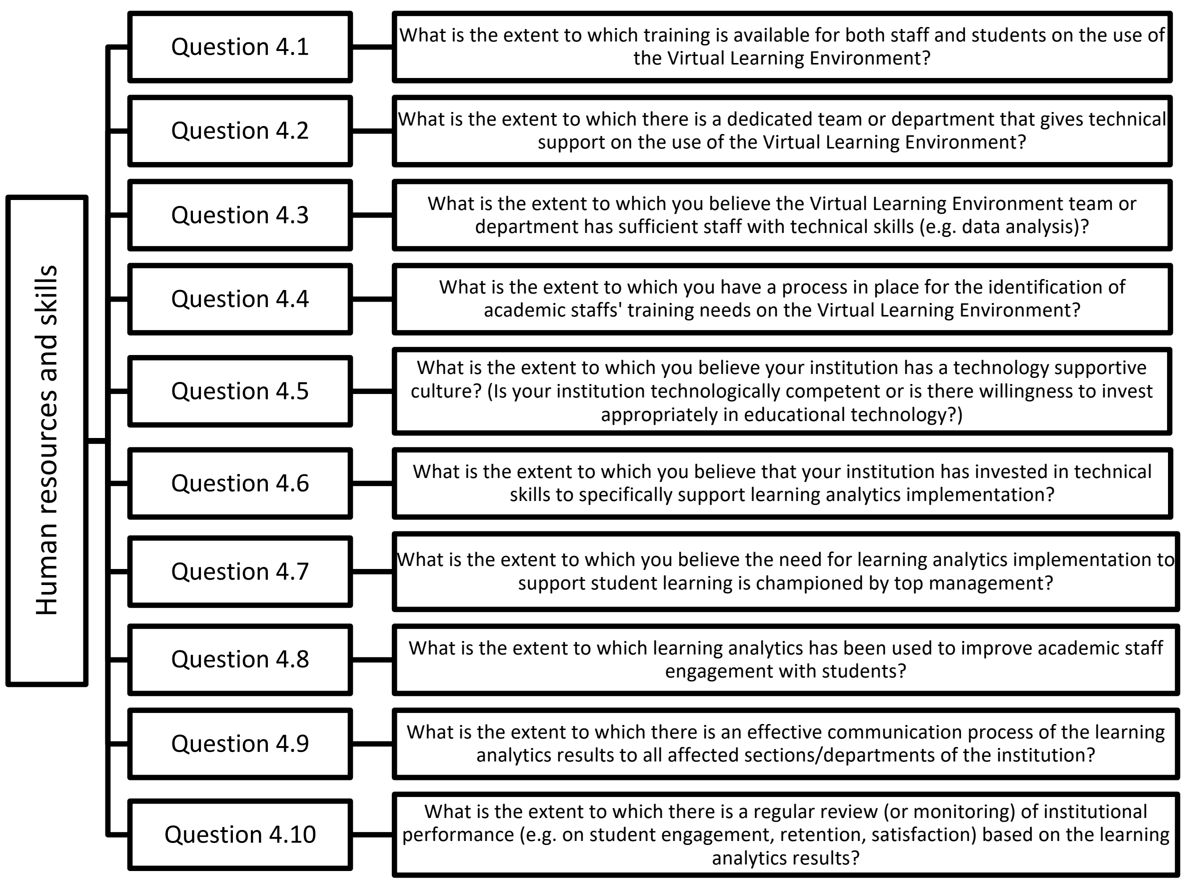


Figure 5-7: Human resources and skills component assessment questions

5.2.3 Summary

The performance measurement tool is an integral part of the LA maturity assessment framework. Thus, the tool has to be used in conjunction with the maturity model and road map recommendation. The importance of the tool is that it helps position or map the progression of an HEI on the different aspects of LA which then forms as a basis for identifying the maturity level in the model. The tool maps the position of an HEI through using assessment questions on the process, infrastructure, data and human resources and skills, important components for LA implementation. It is the resultant mapping of an HEI against these components that help identify the level of LA maturity to guide the recommendations for progression in LA implementation. The road map recommendation is discussed next.

5.3 Road Map Recommendation

5.3.1 Overview

The road map recommendation is the third component of the maturity assessment framework. The road map has been developed to serve as a guide that can foster progression in LA implementation along the LA maturity levels identified in the maturity model. Thus, the road map recommendation provides the evaluation (policy-oriented) component of this research that is aimed at providing information, based on the research findings, that is useful in making the decision (Silverman, 2016) about LA implementation.

Six recommendations are suggested that can serve as a guide to taking action. These include education and awareness, infrastructure and development, LA functional tools, LA pilot project initiation, LA institutional roll out and LA optimisation. Each recommendation has an underlying question that needs to be addressed. The suggested supportive activities to help address the question are suggested and the desired outcome elaborated. **Figure 5-8** shows the developed roadmap recommendation. The next section discusses these recommended steps.

ROADMAP Recommendations

	1. Education and Awareness	2.Infrastructure and Development	3. LA function	4. Initiate LA pilot project on specific course	5. Business case development	6. Full implementation and optimisation
Key questions	How is the LA awareness?	Is the infrastructure supportive?	Can LA be functional?	Can LA project be piloted?	Are the benefits feasible for full project roll out?	Can LA be optimized?
Activities	1.1 Assign team leader. 1.2 Form the team. 1.3 Develop training material. 1.4 Give training to staff. 1.5 Give awareness seminars. 1.6 Evaluate different VLE. 1.7 Provide LA demonstration. 1.8 Select a specific VLE .	2.1 Install hardware and software for the selected VLE. 2.2 Input courses information in VLE. 2.3 Register students in VLE. 2.4 Use VLE in courses delivery. 2.5 Ensure capturing ALL data in VLE.	3.1 Install LA software I. Integrated with VLE platform. II. Establish interface between VLE extend LA software. 3.2 Ensure the availability all LA tools and method. 3.3 Ensure the availability of the minimum data to start LA activities.	4.1 Select a course to be a pilot project. 4.2 Perform the initial LA essential activities. 4.3 Evaluate the required detail LA activities to improve learning services.	5.1 Measure tangible benefits from pilot project. 5.2 Present a detail case to the university executives. 5.3 Detail plan to roll out the use of LA in all programmes.	6.1 Start rolling out the applications of LA in all courses. 6.2 Convert the result of LA into knowledge to support learning services. 6.3 Diffuse and share the results and good practices.
Outcomes	Increased education and awareness	Supportive infrastructure investment and development	Implementation of LA supportive tools	Pilot LA project	Full LA project implementation	Optimised LA project

Figure 5-8 Roadmap Recommendation

5.3.2 Phases

Six steps have been recommended to support the progression towards making an HEI ready for LA implementation to fully implementing and supporting LA. The ultimate desired outcome should be the optimisation of an implemented LA project, thus reading the maturity level 5. At this phase, the potential benefits of LA are more realisable.

5.3.1.1 Education and awareness

An institutional wide awareness and education of LA are necessary to set the grounds for the successful implementation of a LA project. As such, deliberate steps to build awareness of what LA is and the benefits that it can offer is necessary. To build this awareness, training can be provided to staff and key teams to spearhead the process can be formed. The desired outcome here is increased education and awareness of LA. This involves also educating potential users on how LA integrates with the existing LMS/VLE. Educated and knowledgeable staff pose less resistance to technological change (Hommel et al., 2019; Khalil and Ebner, 2015). This is key to developing a technology supportive culture.

5.3.1.2 Infrastructure and development

With a technologically supportive culture established, the next phase would require that an HEI build capacity for LA in its infrastructure. In this respect, the underlying question being addressed is on how effective and supportive the existing infrastructure is. One of the key aspects for successfully implementing LA is that the existing VLE/LMS must be fully functional (Arroway et al., 2016; Leitner et al., 2017) to support the data measurement, collection, analysis and reporting process. As such, investment in infrastructure which could include installation of software for VLE and establishing a specialised department or team to provide technical support and maintaining the VLE is imperative. The expected outcome is a robust and supportive infrastructure on which LA can be built on.

5.3.1.3 Learning analytics function

Having developed a technologically supportive culture and enhanced the institutional capacity through supportive and functional infrastructure, an HEI should be in a position to start the implementation process for LA. Thus, the existence of a functional VLE/LMS should be capturing sufficient data needed for LA. To facilitate this, LA tools and applications need to be installed. This is because LA goes beyond a descriptive and diagnostic analysis of data to more advanced predictive and prescriptive analysis. As such, LA tools that can employ the different LA techniques are needed (see section 2.9). Further, the LA software should be integrated with the existing LMS/VLE to increase efficiency and functionality. One the LA tools are available, an HEI can move to the pilot phase.

5.3.1.4 Initiative pilot project on a specific course

The desired outcome in the pilot phase is the successful implementation of the LA project to a selected part or course of an HEI that can justify or show the benefits of LA. In this phase, the functionality of the LA software and its interface with the VLE can also be tested and monitored. In the end, the benefits of the LA should be perceived as exceeding the associated costs. This means attaining a positive return on investment. As highlighted in section 2.11, one of the challenges in LA implementation was the inability to show or provide evidence of a positive return on investment. Thus, LA must be implemented efficiently and effectively through first a pilot study that can provide evidence to support full-scale implementation.

5.3.1.5 Business case development

The desired outcome in this phase is the full-scale implementation of LA across the HEI. This, however, is dependent on showing the potential benefits that could accrue to the institutional from the results of the pilot study. The supportive activity for this phase requires detailing a full roll-out plan of the implementation. Importantly, commitment from management and appropriate leadership support should have been established. At this stage, an institution should be able to see the desired benefits of having implemented a LA project. This can be reflected through aspects such as student retention rates, student performance and engagement. Thus, more informed decisions based on the results from the LA would be taken that enhance the student experience, satisfaction, performance, engagement and overall success.

5.3.1.6 Full implementation and optimisation

The desired outcome is a fully implemented and optimised LA project. This requires that the institution fully integrates its LA software within the VLE/LMS platform and also interfaces these to institutional performance evaluation. The aim is to ensure that organisational effectiveness occurs through improvements made to aspects of learning and teaching. This requires that LA is rolled to all course of an HEI and there is a deliberate action taken to make corrective decisions based on the LA results. In addition, good practices need to be promoted and mechanisms for identifying areas that require improvement for the full functionality of LA are operational. Leadership and strategic direction is necessary for this to occur (Newland and Trueman, 2017).

5.3.2 Summary

The roadmap recommendation has identified 6 phases that could be followed in the LA implementation process. It is necessary to acknowledge that HEIs can be at different levels of LA maturity. As such, some suggested activities would already be in place for some HEIs while not yet implemented at all for others. As such, the roadmap recommendation could help to identify what is currently missing or what needs attention. For instance, an HEI could have installed LA software in the desire to obtain benefits from it. However, the culture (and attitude) towards the LA project could be negative. Therefore, such an HEI would have to first build up a technology supportive culture to advance the LA project implementation. Conducting workshops, seminars and demos could be used to build awareness and develop an understanding of why embarking on a LA project are necessary.

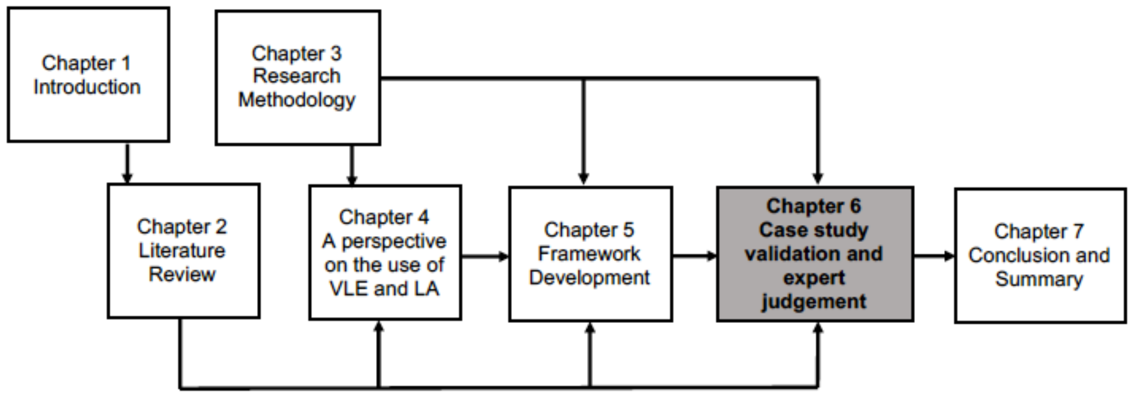
5.4 Chapter summary

This chapter was aimed at outlining the developed LA maturity assessment framework. The framework is composed of three interrelated components: the maturity model, the performance measurement tool and road map recommendation. The application of the framework to any HEI should embrace all three components.

The development of this framework comprises a significant contribution to this study. As highlighted in section 2.13, there is a lack of a comprehensive framework on LA in VLE in HEI that is focussed on the learning process and learners specifically. Thus, this study aimed to develop such a framework that could be utilised to different educational contexts that recognise that HEIs could be at different levels of LA maturity, with some not even started the implementation process. Thus, the framework provides some guidelines on how progression could be made in LA implementation.

The next chapter is aimed at validating the developed framework. This is done through case studies and expert judgements.

6 CASE STUDY VALIDATION AND EXPERT JUDGEMENT



6.0 Introduction/overview

Phase 6 of the multi-phases research methodology involves case study validation and expert judgment (see section 3.4). This phase was aimed at validating the developed LA maturity assessment framework (i.e. maturity level model, performance measurement tool and road map recommendations) outlined in chapter 5. The importance of this phase is that it tests the validity and applicability of the framework to different institutional contexts. The validation process adopted two approaches. The first approach employed a case study strategy in which HEIs were selected in different educational (country) contexts. The approach helped to highlight the applicability of the framework to different institutional as well as educational and regional contexts, thereby demonstrating the generalisability and universality of the framework. The second approach utilised expert judgments which involved a critiqued of the developed LA maturity assessment framework. Expert judgment is an important aspect to the validation process considering the nature of LA research as new field still in the early developmental stage. The next section presents findings from first approach.

6.1 Finding from case study validation

Two HEIs in different educational (country) context were selected in this validation process. The first HEI selected was Kuwait's Public Authority for Applied Education and Training (PAAET), one of the largest HEIs in the Middle East. The second HEI selected was the United Kingdom's Cranfield University. The importance of the two different educational contexts would help highlight an emerging and developed country context, demonstrating in part, the institutional capacity development for LA implementation that HEIs need to undertake.

The case study validation process started first with the application of the performance measurement tool (see section 5.2). This tool helped to position the maturity level of the HEI through the composite scoring in the four key perspectives: process, infrastructure, data and human resource and skills. The scoring in each of these components is presented first before the composite scoring in order to identify key areas that the HEIs need to build capacity for LA implementation. The case study validation results from PAAET are presented next.

6.1.1 Kuwait context – (PAAET)

PAAET, a HEI located in Adailiyah, Kuwait, was established in 1982 aimed at developing and upgrading national skills required to meet the demands created by the country's industrial and economic development. It's one of the largest HEI in the Middle East with over 58,000 students (Arab Times, 2018). The composition of these students is all undergraduates (no postgraduates) as the HEI vocational and technical training needs. The HEI has four main colleges: College of Basic Education, College of Business Studies, College of Technological Studies, and College of Health Sciences. Besides these four colleges, there are training institutions directly affiliated with PAAET such as Nursing Institute, Vocational Training Institute, Constructional Training Institute, Industrial Training Institute, the

Higher Institute of Energy and the Higher Institute of Telecommunication and Navigation (PAAET, 2020).

The LA maturity assessment framework was applied to this HEI in order to position it within the developed five maturity levels (basic, developing, functional, advanced and optimised) (see section 5.1) and also make road map recommendations based on the identified maturity level (see section 5.3). The total number of PAAET participants in the validation process was ten (10). These participants had previously been involved in the field study phase (see section 4.1.3). The advantage is that the selected participants were already aware of the research project's aim from the field study interactions. The details of the participants are shown in **Table 6-1**.

Table 6-1: Details of PAAET validation participants

No.	Position	Job type
1	Associate Professor of office technology	Academic
2	Assistant Professor, Department of Family and Consumer Sciences	Academic
3	Associate Professor in the Department of Civil Engineering, College of Technological Studies	Academic
4	Assistant Professor in the Department of Mechanical Engineering (Manufacturing) in the College of Technological Studies	Academic
5	Assistant Professor, Department of Law, College of Business Studies	Academic
6	Assistant Professor, Department of Petroleum Engineering, College of Technological Studies	Academic
7	Associate Professor in the Department of Manufacturing Engineering Technology, College of Technological Studies	Academic
8	Head of Support and Support Unit at the Computer Centre	Administrator
9	Deputy Director of the Computer Centre	Administrator
10	Head of the Information Technology Unit at the Computer Technology Centre	Administrator

6.1.1.1 Performance measurement scores

6.1.1.1.1 Process scores

The application of the process assessment questions (checklist) to PAAET produced the results shown in **Table 6-2**. These are graphically depicted in a radar chart in **Figure 6-1** in order to give more context.

Table 6-2: Process assessment scores

Questions	Scores
RQ1	2
RQ2	1.7
RQ3	1.9
RQ4	1.7
RQ5	1.6
RQ6	2.6
RQ7	1.6
RQ8	1.9
RQ9	1.9
RQ10	1.9
Total	19
Process average score	**1.9**

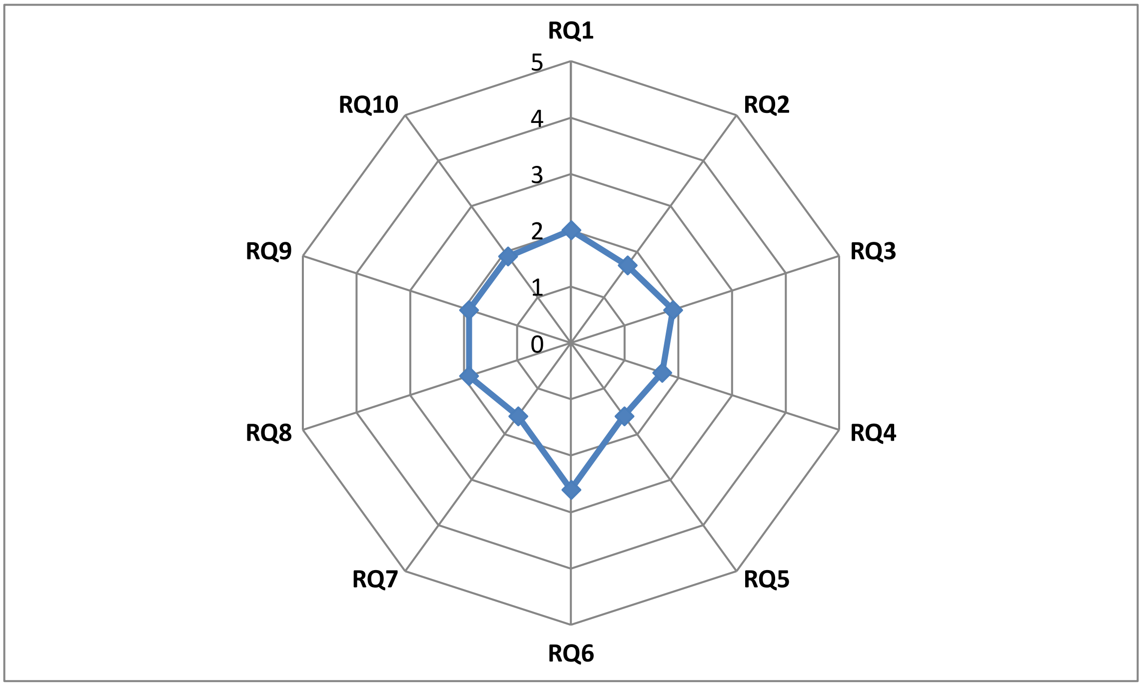


Figure 6-1: Process scores

The results have revealed the existence of a process for capturing students' behaviour, satisfaction and performance in the learning environment which could provide a source of rich data (Aguilar et al., 2019; Waheed et al., 2020). However, this process for capturing students' behaviour, satisfaction and performance is not (fully) integrated in the learning design. Nonetheless, some benchmark metrics seem to exist for evaluating these students' aspects, including a standard process for monitoring and taking action. In addition, there is no clearly established department or team that is dedicated to the control, management and maintenance of the learning processes as depicted by the RQ5 score.

An institutional process and structure for identification and designing of new degree programmes is generally followed despite the adhoc approach to planning these new degree programmes. The HEI is mainly still in the process of developing institutional wide policies for implementation of new degree programmes.

6.1.1.1.2 Infrastructure scores

The HEI's infrastructure assessment question scores are presented in **Table 6-3** and graphically depicted in **Figure 6-2**. The existence of a VLE platform, Moodle (an open source VLE) is well acknowledged at an institutional level. Most of the components of the VLE (i.e. curriculum mapping, student tracking, online support for both teacher and student, electronic communication and internet links to outside curriculum resources) are also functional throughout the university. In addition, some adhoc training and support is provided on using the VLE. Most of the VLE support, however, is available on special request.

Table 6-3: Infrastructure assessment scores

Questions	Scores
RQ1	4.7
RQ2	2.6
RQ3	1.9
RQ4	1.9
RQ5	1.2
RQ6	1.1
RQ7	1
RQ8	2
RQ9	1
RQ10	1.4
Total	18.8
Infrastructure average score	**1.88**

Further, whilst Moodle is institutionally used, the HEI has not yet developed a mechanism to evaluate its performance. As such, a comparison of additional aspects that a non-open source VLE could offer would not easily be evaluated (Dahlstrom et al., 2014; UCISA, 2019). For instance, Suri and Schumacher (2008) compared staff perception of open source vs proprietary VLE and found that whilst proprietary VLE (such as Blackboard) had greater functionality, staff preference was on Moodle which was perceived as more user friendly.

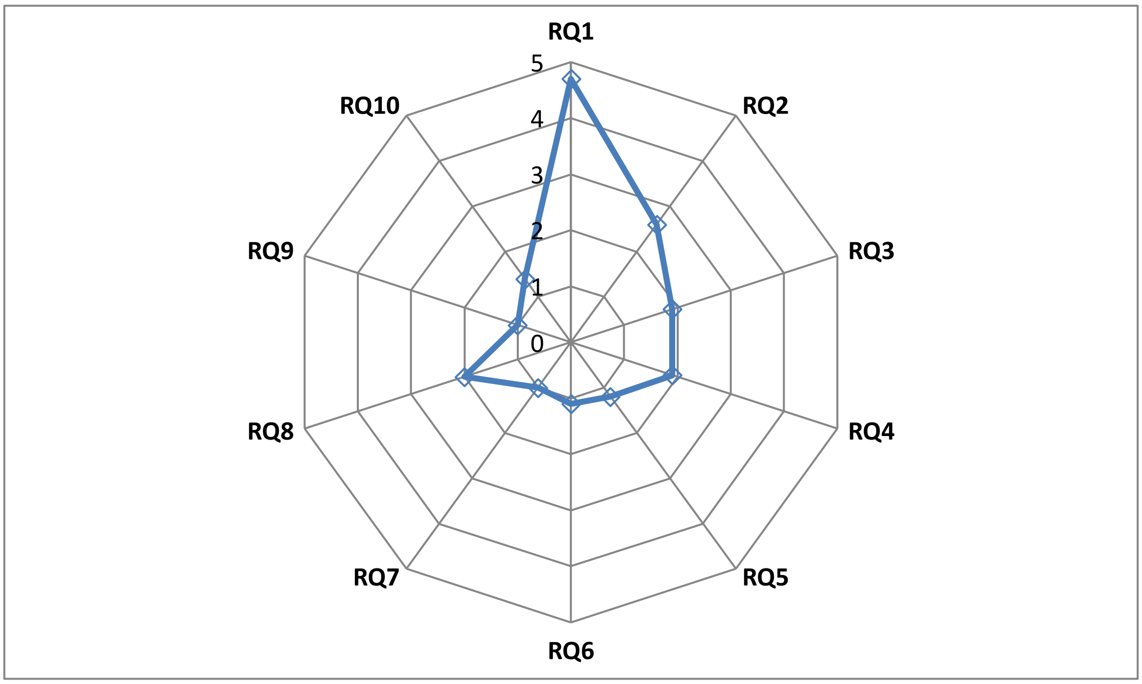


Figure 6-2: Infrastructure scores

The HEI has not implemented any LA nor is it currently considering implementing LA. However, there is some monitoring of aspects such as student performance and retention which represent some basic stages of LA. What can be inferred is the basic aspect of descriptive analysis (addressing questions of what happened) which is performed on an ad-hoc basis. Further, as the HEI invests more in educational technology, it could gradually build capacity of its technological infrastructure that could support LA which currently is low.

6.1.1.1.3 Data scores

The scores for the data related component are presented in **Table 6-4** and graphically represented in the radar chart in **Figure 6-3**. The HEI has plans to have an institutional wide process for analysis of data from the existing VLE. There is a generally an acknowledgement that the current VLE does capture data on students learning experience such as student numbers, student engagement and interaction with the VLE and students' performance on the courses. However, such data has only been descriptively analysed on an adhoc basis to understand what happened e.g. students' performance on the course. As highlighted in section 2.8, most of the data made available from the VLE is static data (Shacklock (2016) in the case of PAAET. The HEI has not actively captured the 'fluid data' (digital footprint data) from the VLE. As a result, there is no active analysis of data beyond descriptive level to even diagnostic levels, for a movement towards LA implementation.

Table 6-4: Data assessment scores

Questions	Scores
RQ1	1.9
RQ2	1.8
RQ3	1
RQ4	1
RQ5	1
RQ6	1
RQ7	1
RQ8	1
RQ9	1
RQ10	1
Total	11.7
Data average score	**1.17**

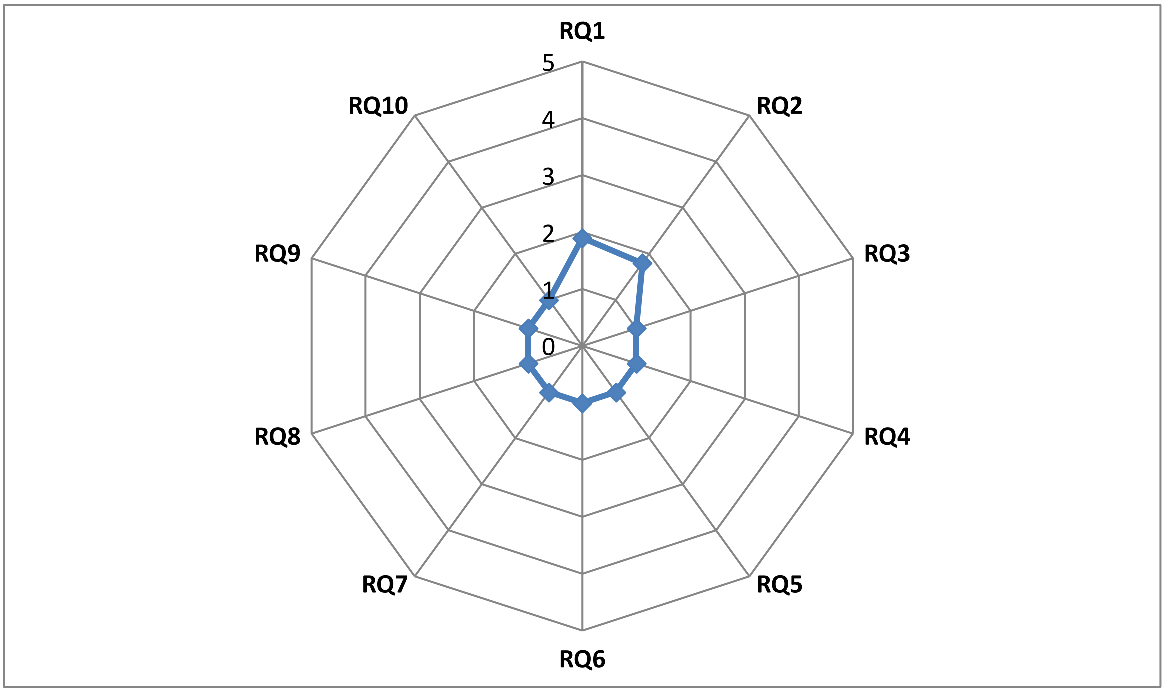


Figure 6-3: Data scores

6.1.1.1.4 Human resource and skills scores

The performance of the HEI with respect to human resources and skills component was highest among the four aspects assessed with an average score of 2.03. The score results are presented in **Table 6-5** and graphically depicted in the radar chart in **Figure 6-4**. Significant to the results is the acknowledgement of the role of the Centre for Computer Technology in the monitoring and maintenance of the functionality of Moodle. This department provides technical support on the use of the VLE. However, training for staff and students on the use of the VLE is generally irregular and on request only whilst the HEI considers developing an institutional wide process for identification of training needs.

In addition, whilst the Centre for Computer Technology is recognised as sufficiently staffed, the need for further training to develop data management and data analysis skills of its staff is acknowledged. The scores also suggest that the HEI has not proactively taken steps to invest in technical skills development to support LA implementation.

Table 6-5: Human resource and skills assessment scores

Questions	Scores
RQ1	2.3
RQ2	3.3
RQ3	1.9
RQ4	2.1
RQ5	2.6
RQ6	1.6
RQ7	2.9
RQ8	1.2
RQ9	1.1
RQ10	1.2
Total	20.3
Human resource and skills average score	**2.03**

Further, the PAAET has shown that it has a relatively supportive technological culture which implies that there is envisaged less resistance to technological change with sufficient support being provided by management too. A technologically supportive culture has been recognised as a key driver for LA implementation (Arroway et al., 2016; Yanosky and Arroway, 2015). However, top management support has to be explicitly requested for in the case of LA implementation as no formal plan or strategy for LA implementation has been communicated.

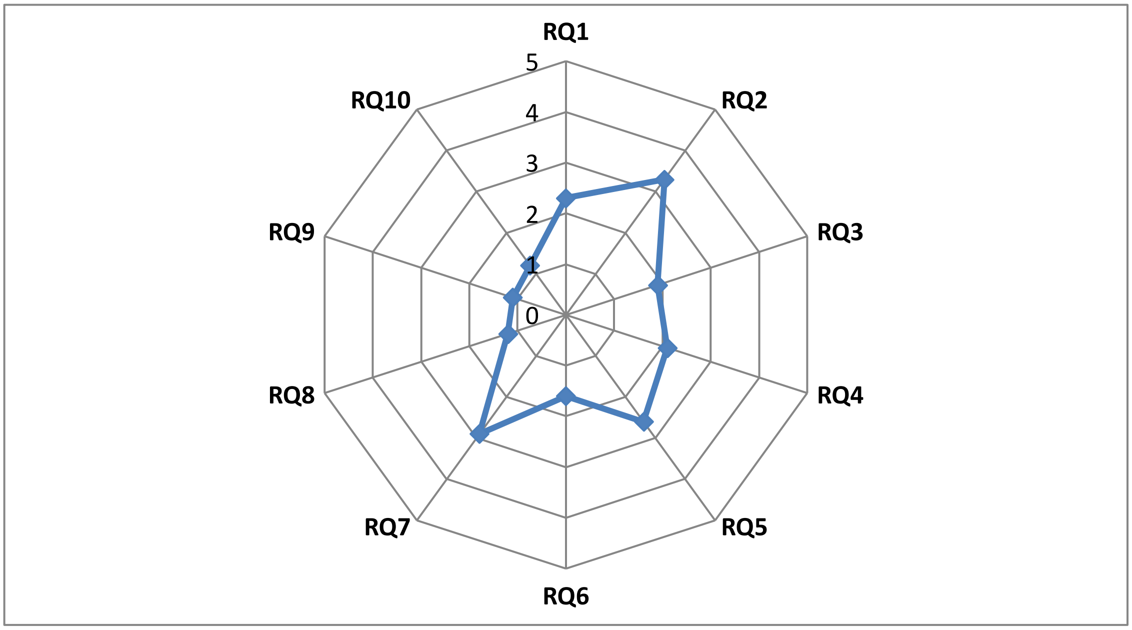


Figure 6-4: Human resources and skills scores

The next section combines these four aspects in order to position the HEI on the LA maturity model.

6.1.1.2 Maturity level

PAAET's performance measurement scores on the four aspects are combined to obtain a composite score that helps position the company on the maturity level. The composite score is presented in **Table 6-6**. The associated radar chart with the LA maturity levels is shown in **Figure 6-5**.

Table 6-6: PAAET composite score

Component	Score
Process	1.9
Infrastructure	1.88
Data	1.17
Human resources and skills	2.03
Composite score	**1.75**

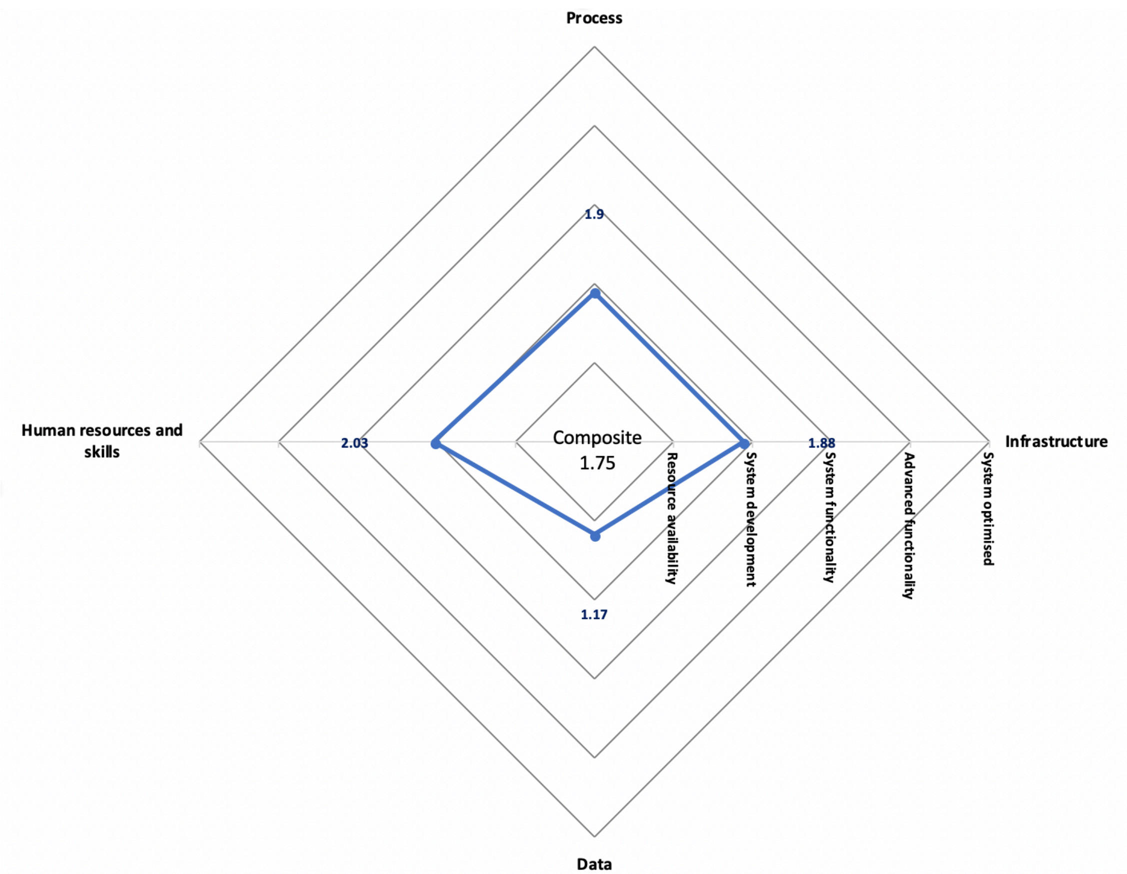


Figure 6-5: PAAET Composite score and maturity level

The composite score of 1.75 arising from the process (1.9), infrastructure (1.88), data (1.17) and human resources and skills (2.03) scores positions the HEI just below the system development level. This is depicted in **Figure 6-5**. The road map recommendations based on the findings above are discussed next.

6.1.1.3 Road map recommendation

Based on the findings from the application of the performance measurement tool and the positioning of PAAET on the system development maturity level, some recommendations can be made.

Education and awareness of the need to enhance the functionality of the existing VLE is needed. Some aspects of this education system are still underutilised. In particular, functionality of the VLE to capture aspects reflecting students' behaviour, satisfaction and performance could be developed further and be fully integrated. This could then be linked to quality assurance where a department or team could be established to control, manage and maintain the learning process so that performance against established benchmarks can be monitored.

In addition, PAAET needs to invest and develop its human resource to enhance particular skills that are relevant for LA implementation (i.e. data management and data analysis skills). Such investment in skills should then be accompanied by the appropriate data capture from a functional VLE. The data capture capacity should be for both static and fluid data which includes the learners' interaction with the VLE (digital footprint data).

The existing technological supportive culture needs to be harnessed as it provides an opportunity to develop the technological capabilities of the institution. With additional education and awareness, the benefits that could accrue from implementing a LA project could be justified. However, as reflected in section 6.1.1.1, top management commitment and support needs to be established. In particular, a proactiveness on the part of management is needed in moving the HEI to be a more ‘data-driven’ institution. This is key especially that investment in technical infrastructure that support LA implementation (i.e. LA tools and applications) requires top management commitment.

PAAET could move to pilot project initiation once capacity is developed. The existence of a department that monitors and maintains the VLE, providing technical support is useful as capacity development can be more directly applied. The staffing levels are already adequate, hence, skills developments, increased VLE functionality and investment in LA tools/application could be relatively easily phased. The benefits of implementing a LA project, however, have to be concretely established to show a return on investment; a problem that exists in many contexts (Herodotou et al., 2019; Newland and Trueman, 2017; Waheed et al., 2020).

6.1.2 UK Context – (Cranfield)

Cranfield University, based in Cranfield, United Kingdom, is a public university specialising in science, engineering, technology and management (Cranfield University, 2020a). It was founded in 1946 as the College of Aeronautics. The university is a postgraduate and research-based institution with over 4,490 postgraduate students and a student to staff ratio of 7:1, one of the best ratios for any university in the UK (Cranfield University, 2020b). The LA maturity assessment framework was applied to this HEI. Apart from being a HEI in a different educational context from PAAET, accessibility consideration was paramount in selecting this HEI. Three (3) participants took part in the validation process. While the number of the validation participants is sufficient to achieve the research objective, more validation participants would have been desired (see section 7.3). The three participants have a wide educational technology knowledge and a good contextual understanding of Cranfield University’s VLE platform. The details of the participants are shown in **Table 6-7**. The validation results are presented next.

Table 6-7: Details of Cranfield University validation participants

No.	Position	Job type
1	Learning Technologist	Academic Support Staff
2	Programme Director	Academic
3	Assistant Registrar	Academic Support Staff

6.1.2.1 Performance measurement scores

6.1.2.1.1 Process scores

The process assessment scores are presented in **Table 6-8** and graphically depicted in a radar chart in **Figure 6-6**. Higher scores are observed regarding processes for identification, planning and implementation of new degree programmes. In addition, there is a specific department/team in charge of controlling, managing and maintenance of the learning process in the institution. This ensures the promotion of HE quality assurance in line with the Quality Assurance Agency for Higher Education (QAA) guidelines (QAA, 2020).

However, the process for capturing students' behaviour, students' satisfaction and students' performance in the learning environment is still not standardised. Thus, whilst student's performance could relatively be monitored, the other aspects regarding their interaction with the VLE are relatively not monitored. Students' satisfaction, for instance, is captured through national surveys (e.g. Postgraduate Taught Experience Survey (PTES), Postgraduate Research Experience Survey (PRES)) and is not integrated into the learning designs. Further, the scores suggest that benchmark metrics for mainly one of these aspects (students' behaviour, students' satisfaction and students' performance) has been satisfactory. Also, where students' performance is below set benchmarks, a process does exist for reviewing and taking corrective action though this seems not standardised across the institution.

Overall, the process assessment score was high at 2.99 reflecting an institutional attention to different aspects of the learning process which contribute to quality higher education delivery.

Table 6-8: Process assessment scores

Questions	Scores
RQ1	3.6
RQ2	4
RQ3	2.6
RQ4	4.6
RQ5	4.3
RQ6	2.6
RQ7	2.3
RQ8	2
RQ9	1.6
RQ10	2.3
Total	29.9
Process average score	**2.99**

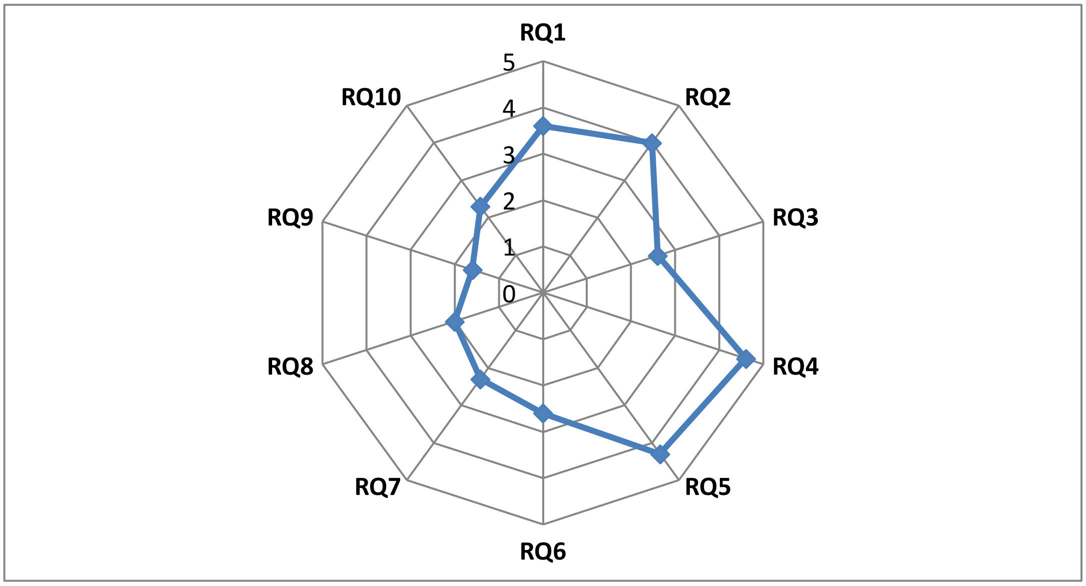


Figure 6-6: Process scores

6.1.2.1.2 Infrastructure scores

Table 6-9 shows the results obtained from the infrastructure assessment questions. These scores are captured in the radar chart presented in **Figure 6-7**. The HEI has a fully functional VLE platform that supports appropriate access to different e-learning information available across the university to all users. The scores also suggest that most of the components of the VLE (i.e. curriculum mapping, student tracking, online support for both teacher and student, electronic communication and internet links to outside curriculum resources) have been implemented or are functional.

Sufficient support (e.g. through training) on the use of the VLE is also available. However, some ad-hoc mechanism for evaluating the successful performance of the VLE platform seems to exist.

The HEI has not implemented any form of LA, nor is there any direct indication that suggest plans to implement LA. However, the scores suggest that the HEI is building capacity of its technological infrastructure that could help support LA implementation if this was considered.

Table 6-9: Infrastructure assessment scores

Question	Scores
RQ1	4.6
RQ2	3.3
RQ3	4.6
RQ4	2.6
RQ5	2.3
RQ6	1.3
RQ7	1
RQ8	1.3
RQ9	1
RQ10	1.6
Total	23.6
Infrastructure average score	**2.36**

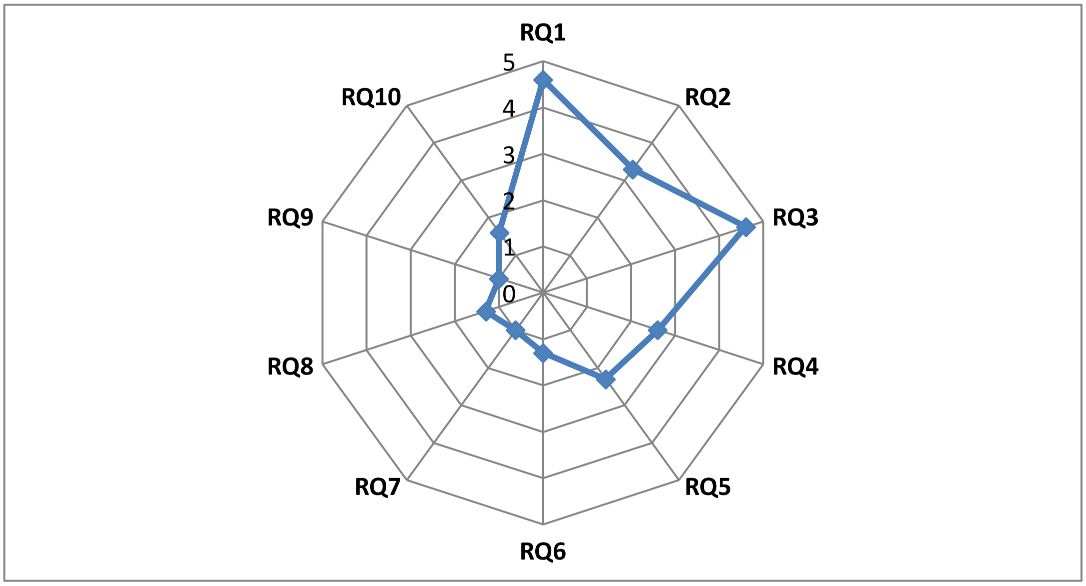


Figure 6-7: infrastructure scores

6.1.2.1.3 Data scores

The results from the data assessment scores are presented in **Table 6-10** and graphically depicted in the radar chart in **Figure 6-8**. The scores suggest the existence of plans to analyse data from the VLE, however, the lack of implementation of LA tools and applications has rendered this not practical. Thus, whilst the VLE could capture data on students' learning experiences (both static and fluid data), no formal analysis is performed. Some ad-hoc descriptive analysis e.g. on students' performance could be undertaken, nonetheless.

Table 6-10: Data assessment scores

Question	Scores
RQ1	1.6
RQ2	1
RQ3	1
RQ4	1
RQ5	1
RQ6	1
RQ7	1
RQ8	1
RQ9	1
RQ10	1
Total	11.6
Data average score	**1.16**

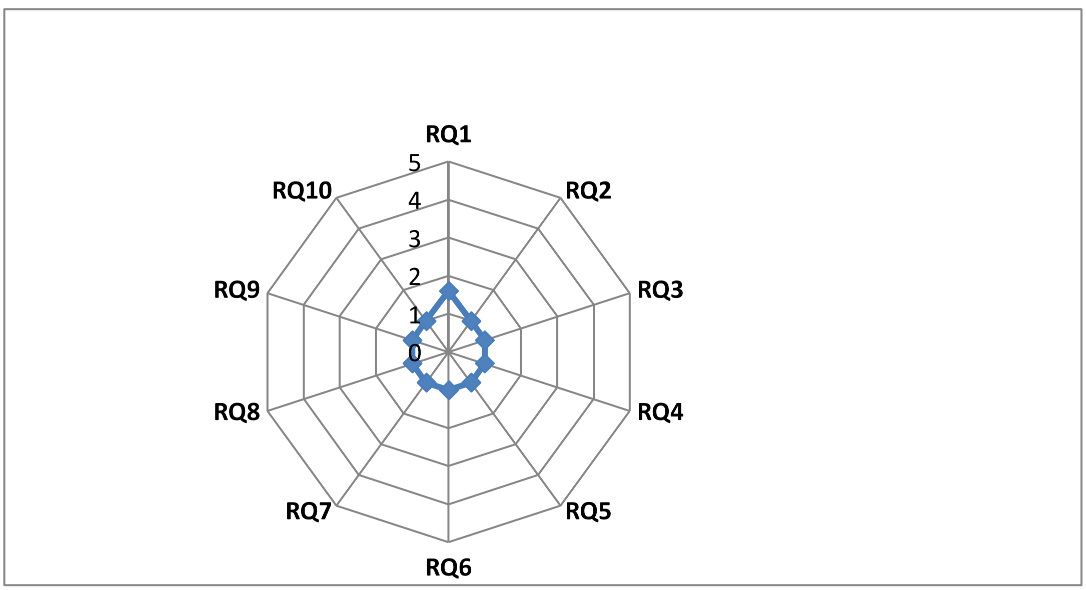


Figure 6-8: Data scores

6.1.2.1.4 Human resource and skills scores

Table 6-11 presents the human resource and skills scores which are then graphically captured in the radar chart in **Figure 6-9**. The scores suggest that regular training is often provided to staff (and occasionally to students) on the use of the VLE. The existence of a dedicated team/department makes the provision of technical support readily available. The scores also suggest that this department/team is sufficiently staffed though still in need of further training investment in data management and data analytics skills if LA is to be implemented.

Further, with respect to the identification of training needs for academic staff on the VLE, the scores suggest that a plan to develop a university-wide standard process is in place though not fully implemented. As such, academic staff's training needs on the VLE are still identified on an ad-hoc basis.

In addition, the HEI has overall a technology supportive culture which implies that the implementation of LA would likely face less resistance with sufficient support from management. However, whilst this is the case, the scores suggest that the HEI has not sufficiently invested in technical skills development that are directed at moving towards LA implementation. If LA was to be successfully implemented, top management commitment to the project would have to be explicit (Arroway et al., 2016; Norris and Baer, 2013).

Table 6-11: Human resource and skills assessment scores

Question	Scores
RQ1	3.6
RQ2	4.6
RQ3	3
RQ4	2
RQ5	2.3
RQ6	1
RQ7	1.3
RQ8	1
RQ9	1
RQ10	1
Total	2.08
Human resources and skills average score	**2.08**

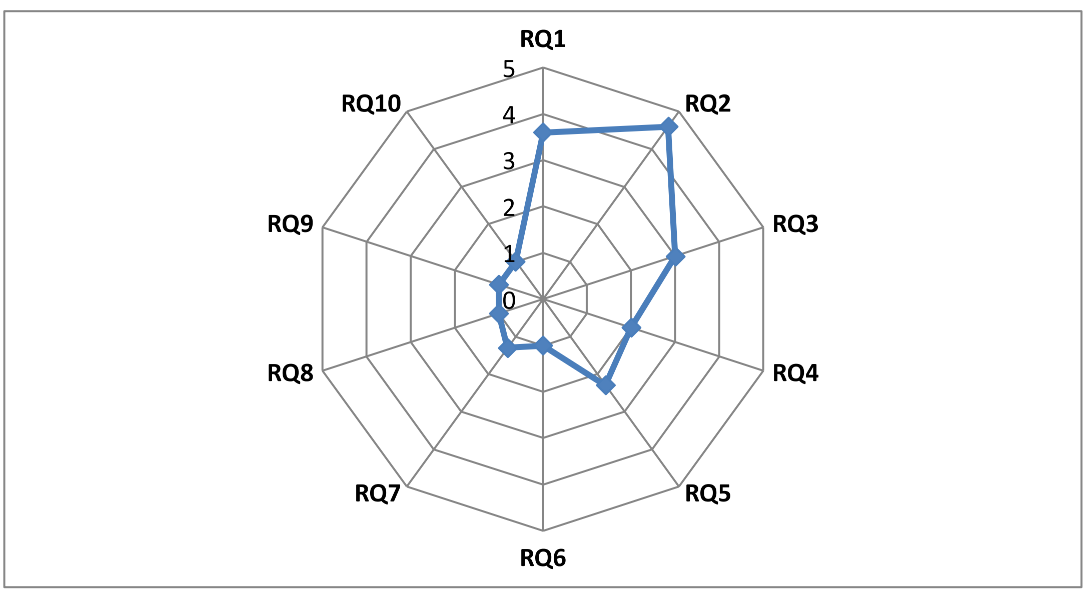


Figure 6-9: Human resources and skills scores

The next section combines the results obtained from the four components in order to position the HEI within the developed LA maturity model.

6.1.2.2 Maturity level

The combined scores from process (2.99), infrastructure (2.36), data (1.16) and human resources and skills (2.08) produce a composite score of 2.15. These are presented in **Table 6-12**. The composite score positions Cranfield University between system development and system functionality maturity levels. This is graphically depicted in the radar chart which shows the LA maturity levels and composite score in **Figure 6-10**. The road map recommendation based on the performance measurement scores and LA maturity level are discussed next.

Table 6-12: Cranfield University composite score

Component	Score
Process	2.99
Infrastructure	2.36
Data	1.16
Human resources and skills	2.08
Composite score	**2.15**

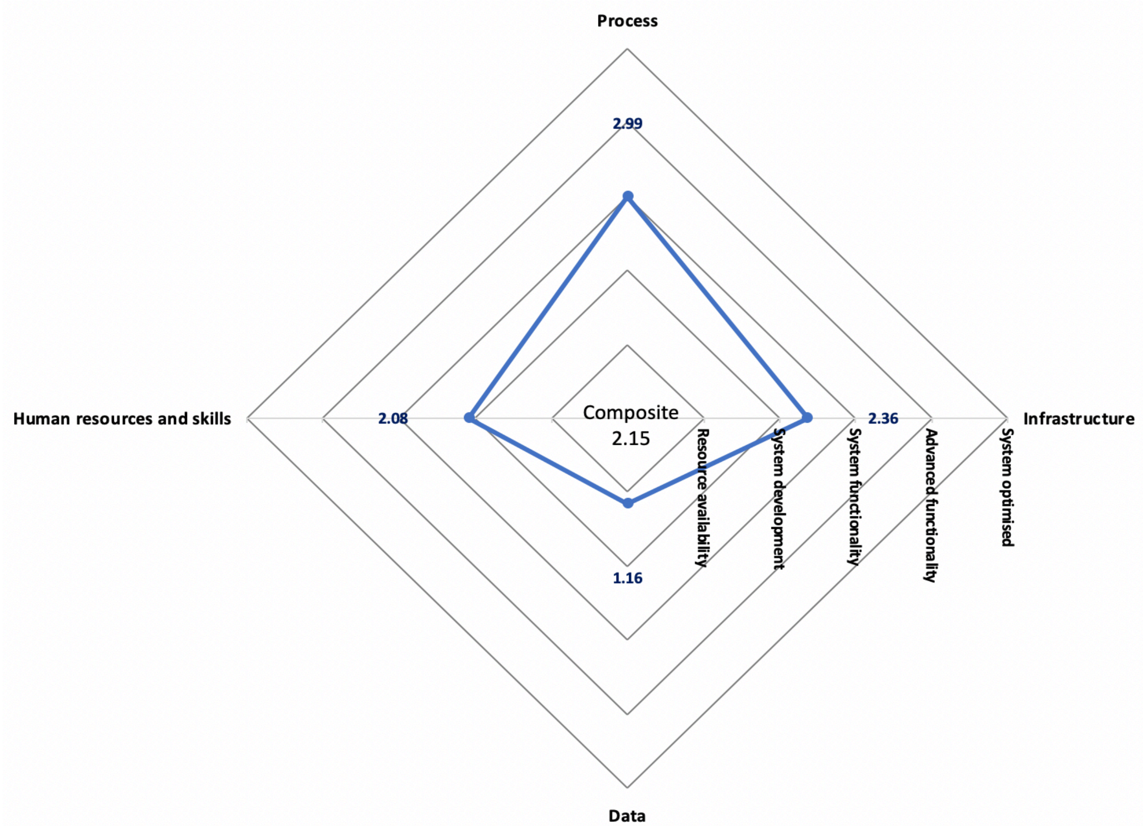


Figure 6-10: Cranfield University composite score and maturity level

6.1.2.3 Road map recommendation

The road map recommendations based on the identified LA maturity level include the further development of the existing VLE to achieve full system functionality that captures all aspects of learners' interaction with the system. Most of the VLE are already functional, thus, capacity building would involve the steps to data capture to make available all digital footprint of the learners' interaction with the VLE.

In addition, investment in training and skills development of technical staff is necessary particularly in aspects of data management and data analysis. This would develop the institution's human resource and skills to enable the implementation and effective usage of LA tools and applications.

The HEI has opportunities that arise from its relatively solid and established processes of learning services which need to be harnessed. This essentially puts the HEI in an advantageous position as the technological supportive culture would foster the investment results of a LA implementation project.

With system functionality which captures data for LA, there should be a proactive commitment from top management to invest in LA tools and applications for a LA project which can be piloted and then later rolled out to the entire institution. As such, more awareness and justification need to be made to top management (for instance, by the Learning Information Technology team and Quality Assurance team) on the benefits that could accrue to university on undertaking such a LA project.

6.1.3 Comparative analysis

A comparative analysis of the two case studies on their performance in the performance measurement tool and position in the maturity level is shown in **Table 6-13** and depicted in the radar chart in **Figure 6-11**. From the comparative results, it’s evident that significant differences exist in two of the components, process and infrastructure.

The significant differences with respect to process and infrastructure is what is contributing to Cranfield University being towards the system functionality level as compared to PAAET which is towards system development. The differences in infrastructures (and processes) might be related to the level of economic development within which these HEI operate in. With respect to process component, the differences might be reflective of the relative national efforts of promoting HE quality. The United Kingdom has an international reputation for high education quality; quality that is government-guaranteed (British Council, 2020).

Interestingly, there is no significant difference observed in respect of data and human resource and skills components in the two HEIs; PAAET and Cranfield University.

This is partly reflective of the findings that both universities have not implemented any LA and thus, not invested much in human resources skills development and also the capture and subsequent analysis of data from the VLEs. In this respect, significant difference was not identified which highlights the lack of employment of LA skills in data analysis. With respect to Cranfield University, in particular, the system functionality of the VLE is high such that rich data which is needed for LA tools/application could easily be retrieved or extracted. This is different to PAAET which still needs to develop its technical infrastructure. As a result, the difference in the performance score was not significant because the human resource and skills existing in the HEIs have not been deployed in the data analysis due to the lack of LA project implementation.

The results obtained from this validation process was instrumental in refining especially the road map recommendation, helping to consolidate the identified key tenets for LA project implementation. For instance, the importance of education and awareness of LA at different LA maturity levels.

Table 6-13: Comparison of composite scores

LA Component	CRANFIELD	PAAET
Process	2.99	1.9
Infrastructure	2.36	1.88
Data	1.16	1.17
Human resources and skills	2.08	2.03
Composite Score	**2.15**	**1.75**

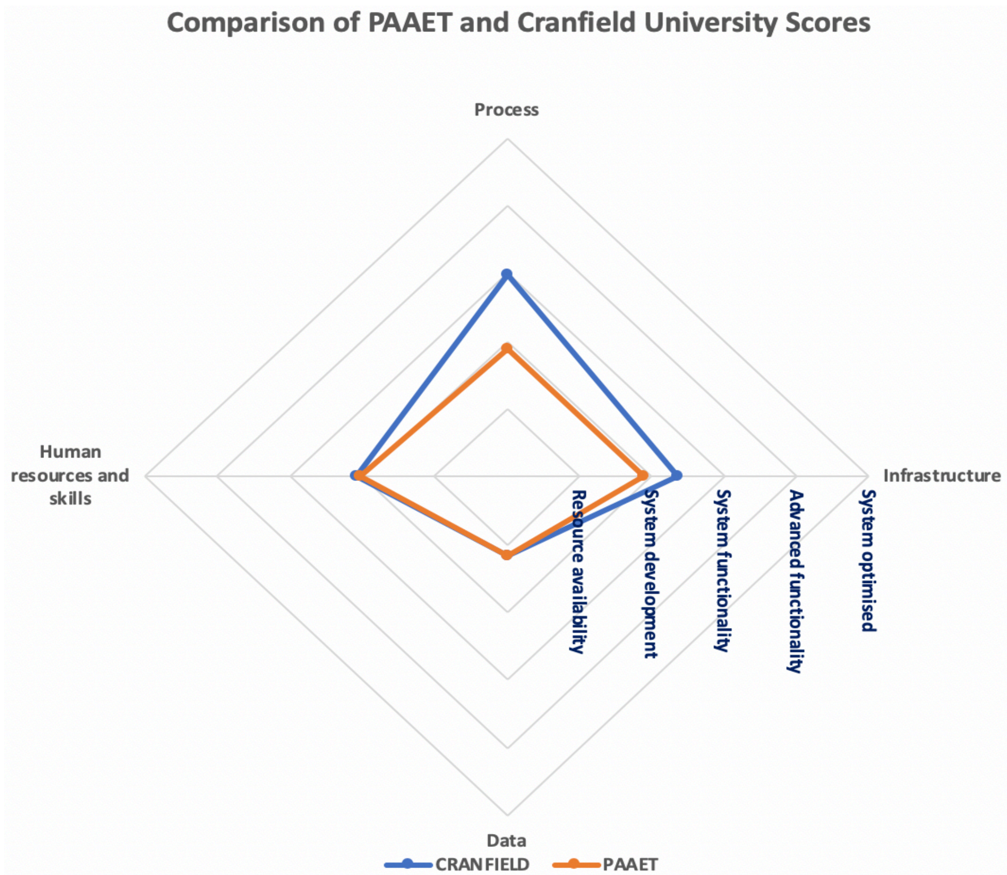


Figure 6-11: Comparative scores of PAAET and Cranfield

The next section discusses some expert judgments on the LA maturity framework.

6.2 Expert Judgment

In addition to case study validation, expert judgment on the developed LA framework was sought. In this respect, the maturity model, performance measurement tools and road map recommendation were availed to different experts in LA in order to obtain their opinions and also evaluate their judgments based on the underlying aim of the developed framework. The expert judgments and critiques help, not only to validate the LA maturity assessment framework, but also provides insights for refining the framework even further. Four experts, from outside the two case studies, commented on the developed LA maturity assessment framework. These experts where identified and recruited applying a snow-balling technique (Titscher et al., 2000) through the network of the validation participants. The experts possess sufficient educational technology knowledge and experience with their vast years of experience. The long experience in the field gives them high level knowledge and insight of how the educational technology landscape (VLE and LA included) has changed. Whilst the aim was to capture more expert views, the four experts successfully interviewed were sufficient to achieve the research objectives. Some verbatim extracts are provided below. **Table 6-14** summarises the experts' background, years of experience, country of origin and qualifications.

Table 6-14: Expert background

No.	Area	Years of Experience	Country	Level of Education
1	Consultancy	14	Kuwait	PhD
2	Consultancy	10	United Kingdom	Professional Qualification
3	Academic and consultancy	20	United Kingdom	PhD
4	Academic	8	United Kingdom	PhD

6.2.1 Positive feedback on the LA maturity assessment framework

The overall judgment on the developed framework was positive. In particular, the contribution of the LA maturity framework to LA in general was highlighted. Some comments in this respect included:

> “LA is still in its early development stage, so any additional insight that can be provided to how this could be developed further is a contribution” (Expert 1)

> “besides the work of Educause, we need LA developmental frameworks such as this one” (Expert 3)

> “as you know, LA is the third wave in the development of instructional technology. We are advancing and any contribution to this advancement is welcome. The framework does make a contribution to this advancement in knowledge” (Expert 4)

One expert also commented on the position of the developed framework relative to the existing framework, stating that:

> “I have in mind the HE maturity framework which identified five levels also, absent/adhoc, repeatable, defined, managed and optimised. I can see that you also have five levels in your framework; which means you are not too distant with the situation” (Expert 2)

Some comments on the performance measurement tool were also positive, such as:

> “the questions are quite comprehensive as they have covered those institutional aspects adequately” (Expert 3)

> “the checklist of questions is very good. They can easily be applied to evaluate performance which is the key consideration here” (Expert 1)

> “limiting the components to four makes this tool more practical. You may need to justify this more” (Expert 2)

With respect to the road map recommendation, some positive comments obtained included:

> “this is key; there is no need to identify a problem if you aren’t going to give a solution. So, a road map recommendation helps complete the picture here” (Expert 2)

> “awareness, awareness, awareness! This is important. Universities are sitting on large data which needs to be exploited. I think capacity they have already. What is needed is awareness so that more can buy into learning analytics” (Expert 1)

> “this is good. The structure of the road map can show what has to be done by first asking an underlying question? The first two questions I think are key: how is the awareness? Is the infrastructure supportive? Once these are addressed, I truly think an institution can move forward with LA implementation” (Expert 3).

> “this is important! It underlies LA advancement. A lot of institutions have not yet adopted LA. So, a guide to help them in the implementation process is welcome. As you might know, different factors have hindered this implementation, one of these is lack of understanding of the whole LA concept. Yes, education and awareness have to be the foundation” (Expert 4)

6.2.2 Experts critique on the LA maturity assessment framework

Some critique of the developed LA maturity assessment framework were also highlighted by the experts which are worthy taking into account as they also support the underlying aim of the framework.

Some critique on the approach to identifying the maturity levels were made which are:

> "well, you have identified five maturity levels which is good. You are then using numerical scores to position educational institutions on these levels. This is generally fine. However, there must be an emphasis that the levels are actually a continuum. Where one level ends and another begins is a blurry and not a clear cut. How do you distinguish a score of 2.75 and 3 for example" (Expert 1)

> "I appreciate the maturity levels, and as I stated, Educause identified five levels too. This does not need to be generic. I suggest that at the lower levels, we make more distinctions as this is where many educational institutions are." (Expert 2)

> "I think leadership is the underlying key. Whether talking about process, infrastructure, data, human resources, you need this as a starting question I think" (Expert 3)

> "The contribution is there yes. I think you need to acknowledge explicitly that analytics can be at different levels: institutional, academic and students/learners. What I see here is both academic and students/learners level of analysis. Then think of the role of LA in each level" (Expert 4)

Another expert commented on the four components used in the performance measurement tool, highlight that:

> "My concern is on whether your four components should have similar weighting to the score. Should infrastructure and data have the same weighting? This is definitely food for thought" (Expert 2)

The expert judgement was insightful and largely show that the developed LA maturity assessment framework is valid. Some critique helped to further refine the framework presented in chapter five. In addition, some of the expert comments helped to identify areas where further work will have to be undertaken (see section 7.4).

6.3 Summary

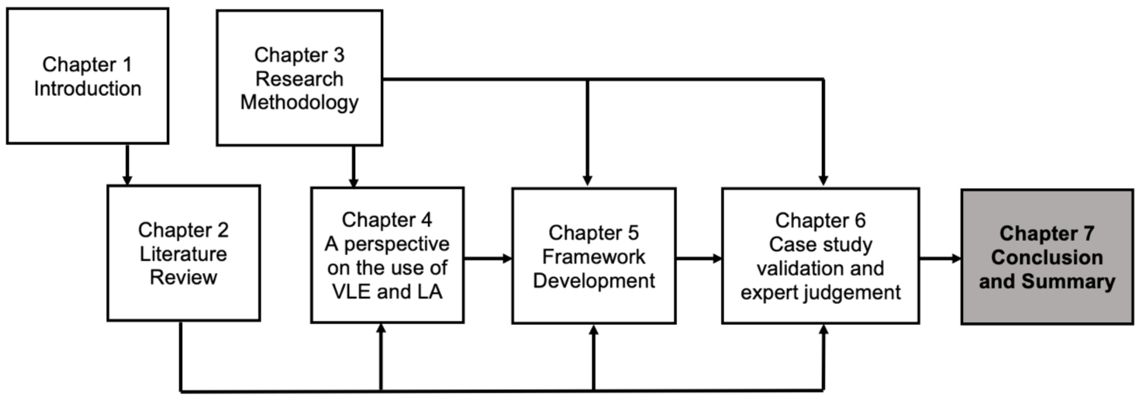
This chapter has presented the validation process incorporated in the development of the LA maturity assessment framework. This represented phase 6 of the multi-phases research methodology presented in section 3.4.

The application of the framework to an emerging and developed country context of Kuwait and United Kingdom respectively, provides some assurance regarding the validity of the developed framework. The application should follow the employment of the performance measurement tool, then positioning of a HEI on the maturity model and then utilising the road map recommendation to guide how progression could be made in LA implementation plans.

Expert judgments also provided positive feedback on the development framework indicating its overall validity. Some critique obtained helped to further refine the framework whilst acknowledging its underlying aim.

The important implication from the developed LA maturity assessment framework to any HEI is that it can help in the development of a high-level LA implementation action plan, through the identification of the institution’s maturity level (using the performance measurement tool) and then consulting the roadmap recommendation. The next chapter provides a discussion and conclusion.

7 DISCUSSION, CONCLUSIONS AND FURTHER WORK



7.0 Introduction

This chapter provides a summary of the research project, highlighting how the research objectives have been achieved. The contribution to knowledge in undertaking this research project are then discussed before suggesting areas for future work based on the limitations of this study. A summary discussion of the research project is presented first with respect to the research objectives.

7.1 Discussion

7.1.1 Research summary

This research was aimed at developing a framework that could be utilised to assess the maturity level of LA in VLE in HEIs. The assessment of the maturity level of LA in VLE in HEIs contributes to enhancing the educational learning programmes and the academic services offering to the learners. The developed LA maturity assessment framework includes measurement of the performance of an HEI as well as road map recommendations to help advance the HEI’s maturity level. Thus, the developed framework not only identifies the LA maturity level through employing a developed performance measurement tool, but also makes road map recommendations on progressing LA implementation in an HEI. Successful LA implementation enhances the teaching and learning processes (Larrabee Sønderlund et al., 2019; Sclater et al., 2016; Viberg et al., 2018).

The study had five research objectives which have been addressed as follows.

7.1.1.1 RO1 – Understanding the use of LA in VLE in HEIs

The first research objective was aimed at "gaining an understanding of the use of LA in VLEs in order to capture the good practices of learning services in HEIs". In achieving this objective, an extensive literature review was undertaken which highlighted that is no one single universally accepted definition of LA, with contributions made from a wide range of disciplines. LA is a relatively new research area (Larrabee Sønderlund et al., 2019; Viberg et al., 2018) and integrates the research and methodologies that are related to data mining, social network analysis, visualisation data, machine learning, learning sciences, psychology, semantics, artificial intelligence, e-learning and educational theory and practice (Dawson and Siemens, 2014; De Moraes et al., 2016). LA involves the utilisation of insights gathered from data from the education learning environments in order to make interventions that improve teaching and learning, and also generate actionable intelligence which informs appropriate interventions (Campbell et al., 2007; Clow, 2013). However, LA is still generally underutilised in HEIs (Alexander et al., 2019; Newland and Trueman, 2017; Parnell et al., 2018; Sclater and Mullan, 2017; Shacklock, 2016; Viberg et al., 2018) despite an increase in the number of HEIs working towards implementation (Newland and Trueman, 2017). The key drivers have been the growth in online learning and increased demand for HEIs to measure, establish and develop performance (Ferguson, 2012; Sclater et al., 2016; QAA, 2020). However, technical, financial, organisational and ethical challenges have hindered LA implementation in HEIs.

An identified gap in the literature is that most HEIs do not know where to start from when considering a LA project or the progression path to follow (Alexander et al., 2019; Newland and Trueman, 2017; Parnell et al., 2018; Sclater and Mullan, 2017). Thus, the aim of this research project was to contribute by developing a LA maturity assessment framework that focusses on LA in VLE in order to enhance the educational learning programmes and the academic services offered to the learners.

7.1.1.2 RO2 – Obtain stakeholder perspectives on the use of VLE and LA potential

Developing upon the understanding obtained from the extensive literature review, the second objective was "to conduct a field study in order to obtain stakeholder perspectives on the use of LA to improve learning services in HEIs". Thus, in order to accomplish this objective, the research process included undertaking a field study in order to obtain an overall perspective on the use of VLE/LMS in the learning process. As the research focus is on LA in VLE that focusses on user interactivity, the perspective of students, academic staff and academic support staff was obtained. An online survey was utilised for students with 135 students taking part whilst face to face interviews were conducted with 14 academic staff and 3 academic support (system administrators) from PAAET, Kuwait.

The perspective from students showed that in general, the VLE/LMS is adequate, in terms of functionality, availability, user friendliness, collaborative, aesthetics, simplicity, security, privacy, to support the learning process. Further, the perspective obtained from academic and non-academic staff was the underutilisation of the functionality of the VLE/LMS. The usage of the VLE/LMS was mainly for course content delivery, providing access to learning materials for students. Some level of data analysis (mainly descriptive and diagnostic) existed though no advanced analytics tools had been implemented. In addition, different aspects that show commitment to system functionality (necessary for LA project implementation) were mainly absent reflected by the general lack of leadership, strategy, vision, infrastructure and resources. The general awareness of LA and its associated benefits to an HEI was lacking.

7.1.1.3 RO3 and RO4 – Developing LA maturity assessment framework

Research objective three was "to develop a framework of maturity level on the use of LA in VLEs to support learning services in HEIs" while research objective four was "to develop road map recommendations on the use of the LA in VLEs to support learning services in HEIs". In order to achieve these two objectives, the adopted multi-phases research methodology helped to facilitate the development of the LA maturity assessment framework. In this respect, the knowledge and understanding gained from the extensive literature review and insights from key stakeholders, was instrumental in the development of the framework.

The developed LA maturity assessment framework has three components: maturity level model; performance measurement tool, and the road map recommendation. The performance measurement tool is applied to assess the performance of an HEI in four aspects: process, infrastructure, data and human resources and skills. The composite performance of an HEI in all the four aspects helps to map the HEI's LA maturity level along the five levels: resource availability (level 1), system development (level 2), system functionality (level 3), advanced functionality (level 4) and system optimisation (level 5). The positioning of an HEI on the LA maturity level based on the performance in the performance measurement tool helps in developing road map recommendation.

The developed road map recommendation provides a useful guide on the activities that an HEI should undertake with desired outcomes. For instance, one of desired outcomes is increased education and awareness on LA which could be accomplished through training workshops, LA demonstrations and team assignment. The general lack of awareness about LA was identified in the literature (and in the field study) as contributing to the lack of LA implementation (Hommel et al., 2019; Khalil and Ebner, 2015; Newland and Trueman, 2017; Shacklock, 2016). Education and awareness need to be supported by an appropriate investment in infrastructure development that should support LA implementation (Arroway et al., 2016; Leitner et al., 2017).

7.1.1.4 RO5 – Case study validation and expert judgment

The fifth research objective was "to validate the developed LA maturity assessment framework through case studies, and also evaluate it through expert judgment". As such, this objective was accomplished through validated the developed LA maturity assessment framework using two case studies: PAAET of Kuwait and Cranfield University of United Kingdom. The application of the framework to different HE institutional contexts showed the relevance/validity and generalisability of the developed framework. The performance of the two HEIs using the performance measurement tool positioned PAAET and Cranfield University towards system development (level 2) and system functionality (level 3) maturity levels respectively. In both case study, education, awareness and skills development were identified as necessary whilst infrastructure development was recommended in the case of PAAET. The system functionality identified in the case of Cranfield University implies that rich data that is needed for LA tools/applications could be relatively easily retrieved or extracted.

Besides the case study validation process, expert judgement was sought which was generally positive, identifying the contribution of the developed framework to LA knowledge which is still in its infancy (Sclater, 2017; Sclater and Mullan, 2017; Shacklock, 2016; Viberg et al., 2018).

7.2 Conclusion

This research project employed a multi-phases research methodology to develop a LA maturity assessment framework, comprising of maturity model, performance measurement tool and road map recommendation, that could be used to assess the maturity level of LA in VLE in HEI in order to enhance the educational learning programmes and the academic services offered to the learners. The maturity model developed comprises of five levels: resource availability (level 1), system development (level 2), system functionality (level 3), advanced functionality (level 4) and system optimisation (level 5). These are represented as basic, developing, functional, advanced and optimised respectively. Using the performance measurement tool, an HEI could be mapped within the five maturity levels based on its composite scores of process, infrastructure, data and human resources and skills components. The performance of an HEI which positions it within the maturity level helps guide road map recommendations.

The research project makes several contributions to knowledge which include:

- Assessing the level of LA maturity can form an important aspect to realising, not only the underutilisation, but also give perspective to how development to full functionality or maturity could be achieved. This is important as Newland and Trueman (2017) identified that unclear objectives and lack of evidence of return on investment was affecting LA implementation in HEIs. The assessment of the maturity level of LA in VLEs is necessary as it would enable HEIs to evaluate their progression to the realisation of the full benefits of a functional LA.
- Another contribution of this research is that whilst existing propositions to assess the maturity of VLE typically consider the software underlying the VLE, the developed maturity assessment framework has a focus on the utilisation of the VLE itself. In this respect, it's not only the software underlying the VLE but the utilisation of the VLE itself that should be the focus. This is significant as the infrastructure to support LA functionality must be robust. Arroway et al. (2016) argue that HEIs must "proactively establish processes, policies, and documentation around LA, including data and infrastructure" (p. 3) in order to realise the benefits of LA. This means having a mature data governance system, information technology (IT) systems and infrastructure support, and adequate human resources (Larrabee Sønderlund et al., 2019) to provide a support base that strengthens the foundations of LA. In this respect, the consideration of the underlying software of the VLE in LA maturity assessment process provides an opportunity to evaluate the integrative capabilities of the

VLE platform for improved student experience also. As such, the contribution is to enhance the effective utilisation of the VLE itself.

- The underlying aim in the development of the maturity assessment framework is so that LA implementation could contribute to improving learning services which results in improved student experience and success. From this perspective, the developed maturity assessment framework could be applied to position the implementation and utilisation of LA in VLE to better understand:
  (ii) the progress made so far in the implementation of LA, and
  (iii) the progression route that provides some guidelines to the direction towards the full functionality of LA in VLE.

  In this way, the importance of the developed maturity framework is that it helps in conceptualising how far (or to what extent) an educational institution has progressed on the implementation of LA to improve student learning. In conceptualising this progression, it is important to recognise also that each step towards a higher level of LA maturity essentially builds on top of the previous stages. The aim is to promote progression towards modelling, prediction and optimisation of learning process (Mah, 2016) in order to improve student experiences. In this respect, student generated data gets used for the prediction of educational outcomes, with the purpose of tailoring education (Junco and Clem, 2015; Viberg et al., 2018) to improve student experiences. This addresses the gap in the literature in showing how LA connects with education (Ferguson et al., 2016).
- This research project also makes a contribution to the LA literature which revealed a gap in that existing attempts at measuring LA maturity do not consider learners (students) as a key factor of the assessment (see Norris and Baer, 2013) making maturity assessment as an isolated aspect from users. This comprises a major flaw because of the lack of focus on user interactivity. This research project addressed this flaw based on the convention that the assessment of the VLE maturity level is to be considered within a wider scope

which involves the user interactivity (Aguilar et al., 2019) with the VLEs. Further, existing studies on measuring the level of maturity mainly focus on developing tools and models for analytics without adequate consideration of how LA connects with education and the changes that the main users (i.e. academic support staff, academic staff and students) want these tools to make to support their everyday learning and teaching (Ferguson et al., 2016). In this respect, Arroway et al. (2016) highlight that for more effective implementation and utilisation of LA, HEI should firstly engage with a variety of stakeholders across units to increase buy-in (and identify new funding sources). Moreover, the factors for LA implementation often cited in the literature (leadership, strategy, organisational culture, organisational capacity and technology) (Brown, 2011; Dawson and Siemens, 2014; Yanosky and Arroway, 2015) are not individually adequate to assess LA maturity; instead, it's the relationship and interaction of these factors (Colvin et al., 2014), which requires further attention when conducting the maturity assessment.

- Further, the maturity framework developed conceptualises progression in the utilisation of LA in VLEs unlike other models that perceive its application/implementation only (Chatti et al., 2012; Lias and Elias, 2011). The relevance of this conception is the recognition of the complexity that underlie LA and the context specific nature of its application by different educational institutions. This perspective supports the multi-phases and multi-theoretical methodological approach adopted in the development of the framework.

7.3 Research limitations

The underlying objectives of the research have been achieved. As elaborated in section 1.3, the research objectives included gaining an understanding of the use of LA in VLEs, obtain stakeholder perspectives on the use of LA, developing and validating a framework for assessing the maturity level of LA, and developing road map recommendations on the implementation of LA in HEIs.

Some research limitations, however, need to be acknowledged in the research process towards accomplishing the research objectives. One inherent limitation arises from the methodological choice adopted. A limitation arises from choosing semi-structured interviews (for academic and academic support staff), instead of other methods, for instance, focus groups with such users. Also, the number of participants/respondents could have been increased at both the field study and framework validation phases. In this respect, more students could have been recruited in the online surveys whilst more academic and non-academic staff could have been interviewed from different HEIs. More expert judgement on the developed framework could have been sought. In addition, only two HEIs were used in the case study validation process with only 3 validation respondents in the case of Cranfield University; thus, more cases could have been explored from different country contexts.

As highlighted by one expert feedback, the performance measurement tool puts equal weighting to the four aspects: process, infrastructure, data and human resources and skills. This might not be the case for each HEIs. In addition, whilst the four components have been identified as significant to LA capacity building, more detailed understanding of these components to address the contributory elements could have been explored further in order to give weightings.

7.4 Future work

Arising from the research limitations identified above is future work that could be undertaken. In this respect, future work could involve more case study validation and expert judgement. These could help further development/refinement of the developed framework.

Future work could also involve examining the performance measurement tool further to highlight whether the contributory role of process, infrastructure, data and human resources and skills components could be analysed and distinctively identified more.

This could help to justify whether a disproportionate weighting is practical or not. In addition, future work could involve advancing the road map recommendations to make the road mapping activities more detailed, thus, even more actionable.

In addition, as LA implementation in HEI is still in its infancy, further work could include expanding the first three maturity levels (basic, developing and functional) to help give a more detailed positioning of HEIs on the maturity level. Its acknowledged that within the same maturity level, different HEIs could still be at different sub-levels. Thus, further sub-divisions within the maturity levels could help give more context to guide road map recommendations.

In addition, a longitudinal timeframe (not cross-sectional) could be conducted to assess the maturity levels and implementation roadmap of HEIs so that lessons can be learnt over time.

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APPENDICES

Appendix A Field Study Methods

Appendix A shows the online questionnaires (Appendix A1) and semi-structured interview questions (Appendix A2) that were used during the field study as discussed in sections 3.4.2 and 4.1. The online survey questionnaire was administered 135 students at the Public Authority for Applied Education and Training (PAAET) while the interviews were conducted with 14 academic and 3 academic support staff at PAAET. The aim was to gain a high-level perspective on the use of VLE/LMS from these key stakeholders.

A.1 Online Questionnaire

Learning Analytics – Student Questionnaire

This questionnaire aims to assess the online learning system used in your institution from a student perspective. All answers are anonymous and will not be linked back to the respondent by any means.

Please indicate how much you agree with each of the following statements by selecting one choice. Please also answer the follow-up question after each statement.

1. Sufficient learning resources for my study are available online
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree
        (i) What is not available which you believe should be?

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2. I can receive technical support on using the online system whenever needed
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree
        (i) How is the support offered/received? What else should be done if not enough?

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3. The online system is user-friendly and accessible to students with minimal training
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree
        (i) What needs to change to make it more user friendly if so?

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4. It is necessary to use the online learning system in order to progress on the course
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree
        (i) Why do you think it is so?

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5. Academic staff encourage the use of the online learning system and make resources available online
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree

(i) How do staff promote using the online learning system? How should they do that if not doing it adequately?

----

6. I feel I am able to use the online learning system confidently
   a. Strongly agree
   b. Agree
   c. Neither agree or disagree
   d. Disagree
   e. Strongly disagree
      (i) Can you describe if training is needed in order to use the system?

----

7. The online learning system also includes interactive tools with peer students and staff
   a. Strongly agree
   b. Agree
   c. Neither agree or disagree
   d. Disagree
   e. Strongly disagree
      (i) Can you describe some of these tools and how you have used them?

----

8. The online learning system works well and the layout and design are consistent and properly maintained
   a. Strongly agree
   b. Agree
   c. Neither agree or disagree
   d. Disagree
   e. Strongly disagree
      (i) Can you describe any issues you may have encountered with the functionality of design of the system?

----

9. The need of the online learning system is evident
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree
        (i) Can you elaborate why you think the system is needed?

----

10. Using the online learning system has made my learning experience at the institution better
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree
        (i) Can you describe how the online learning system has contributed to your experience?

----

11. The online learning system serves its purpose well and its use is self-explanatory
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree

(i) Can you provide any suggestion for improvement?

----

12. The system’s downtime is kept minimal
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree
        (i) How often do you usually encounter downtimes? Do they occur with prior notice?

----

13. The system’s technical issues are kept minimal
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree

(i) Can you describe some of these issues if any?

----

14. I trust that my data in the system are kept safe and private
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree

(i) Can you describe any privacy of security

----

15. I spend a considerable part of my study time on the system
    a. Strongly agree
    b. Agree
    c. Neither agree or disagree
    d. Disagree
    e. Strongly disagree

(ii) Can you describe how long roughly you spend on the system? What do you mostly do when logged in?

A.2 Interviews

A.2.1 Interview Questions with System Administrators (Non-Academic Staff)

Interview Guide

1. Can you briefly describe what the learning management system does for the student and instructor?
2. How is learning analytics conducted? What data are collected and analysed?
3. What are the main benefits of using learning analytics for the stakeholders?
4. How are results provided to the educational and business stakeholders?
5. To what extent can the system answer stakeholders' questions?
6. How does the culture in your institution promote and/or challenge the development of learning analytics?
7. Do you request feedback and/or suggestions from the system users relevant to learning analytics?
8. Does learning analytics provide knowledge that results in significant change in any aspect of the organisation?
9. How are ethical concerned associated with learning analytics addressed?
10. How do you see the future of learning analytics in your institution?

A.2.2 Interview Questions with Academic Staff

Interview Guide

1. Can you briefly describe your uses of the learning management system?
2. Are you aware of any learning analytics plans undertaken by your institution?
3. How does the culture in your institution promote and/or challenge the development of learning analytics?
4. What insights do you get from the information provided to you by the system?
5. Would information provided to you by the system yields change to the course arrangement or something similar?
6. What training is provided for staff and students to use the system?
7. Are there ways to provide your feedback or suggestions to the system administrators for example to add/change features?
8. Are you requested by the management to provide your input that would be used for learning analytics?
9. Is the system sophisticated in the sense that it provides advanced analysis and relevant information?
10. Is it clear that learning analytics is aligned with your institution's vision?

Appendix B Performance Measurement Tool

Appendix B presents the detailed questions of the performance measurement tool discussed in section 5.2. The questions are for each of the four components of the performance measurement tool: process, infrastructure, data and human resources and skills. For each component, there are 10 questions with answers ranging from 1-5. The performance measurement tool is used with the LA maturity model in order to identify the LA maturity level of an HEI.

B.1 Process Assessment Questions

1: Process		
	Level	
1: Process	**1**	**What is the extent to which an institutional process for identification of new degree programme(s) development targets exist?**
	1.1	We do not have an institutional process for the identification of new degree programme development targets.
	1.2	An institution policy for identifying new degree programme development targets has been considered but not implemented.
	1.3	An institutional policy for the identification of new degree programme development targets is being developed.
	1.4	Each department (or school) has its own process for identifying new degree programme development.
	1.5	We have an agreed institutional process with a dedicated team that identifies new degree programme development targets.
		What is the extent to which the institution has a standard approach for planning new degree programme(s)?
	2.1	There is no agreed standard process for planning new degree.
	2.2	Developing a standard approach has been considered but not adopted.
	2.3	The university is in the process of developing an institutional planning policy for new degree programmes.
	2.4	Each department (or school) has its own autonomy in planning new degree programmes.
	2.5	The university has a standard process for planning new degree programmes.

		What is the extent to which there is an agreed institutional structure for designing new degree programme(s)?
	3.1	We do not have a standard institutional structure for designing new degree programmes.
	3.2	The university is considering having an institution wide structure for designing new degree programmes.
	3.3	The university is in the process of developing a standard structure for designing new degree programmes.
	3.4	Each department (or school) has its own structure for designing new degree programmes.
	3.5	We have an standard institutional structure for designing new degree programmes.
		What is the extent to which you agree that there is a standard process for the implementation of new degree programme(s)?
	4.1	There is no agreed process to follow when implementing new degree programmes.
	4.2	The university is considering having an institution-wide process for implementing new degree programmes.
	4.3	The university is in the process of developing an implementation policy for new degree programmes.
	4.4	Each department (or school) has autonomy on the process for implementing new degree programmes.
	4.5	We have a standard process to follow when implementing any new degree programme in the university.
		Is there a specific team (or department) dedicated to the control, management and maintenance of the learning process at the university?
	5.1	There is no department (or team) that is solely dedicated to the control, management and maintenance of the learning process at the university.
	5.2	We are considering having a department or team to control, manage and maintain the university-wide learning process.
	5.3	There is an ad-hoc team that controls, manages and maintains the learning process of the university.
	5.4	Each department has authority and responsibility to control, manage and maintain the learning process.
	5.5	We have a department (or team) with responsibility for the control, management and maintenance of learning process across the university.
	6	**Is there a process for capturing: (a) students behaviour; (b) students satisfaction; (c) students' performance, in the learning environment?**
	6.1	None of the above aspects (a, b or c) is capturing in the learning environment.

	6.2	Only one (a or b or c) is captured in in the learning environment.
	6.3	Two of the three aspects (a & b, a & c, or b & c) are captured in the learning environment.
	6.4	The three aspects (a, b & c) are captured at a departmental or school level in the learning environment only.
	6.5	All the three aspects are captured across the university in the learning environment.
	7	**Is the process to capture: (a) students' behaviour; (b) student satisfaction, and (c) student performance, integrated in the learning design**
	7.1	None of these aspects (a, b or c) is integrated in the learning design.
	7.2	Only one (a or b or c) is integrated in in the learning environment.
	7.3	Two of the three aspects (a & b, a & c, or b & c) are integrated in the learning environment.
	7.4	The three aspects (a, b & c) are integrated in the learning design at a departmental or school level only.
	7.5	All the three aspects are integrated in the learning design across the university.
	8	**What is the extent to which there are agreed benchmarks (targets) in desired: (a) students' behaviour; (b) students’ satisfaction; and (c) student performance, metrics?**
	8.1	No agreed benchmarks (targets) for any of these aspects (a, b or c) exist.
	8.2	Agreed benchmarks (targets) exist for only one of these aspects (a or b or c).
	8.3	Agreed benchmarks (targets) exists for two (a & b, a & c, or b & c) of the three aspects.
	8.4	Agreed benchmarks (targets) exist for the three aspects (a, b & c) at a departmental or school level only.
	8.5	Agreed university-wide benchmarks (targets) exist for the three aspects (a, b & c).
	9	**What is the extent to which your: (a) students’ behaviour; (b) students’ satisfaction and (c) students’ performance, metrics against the benchmarks have been satisfactory?**
	9.1	None of the three aspects' (a, b & c) metrics are satisfactory.
	9.2	The metrics on only one of these three (a or b or c) against benchmarks have been satisfactory.
	9.3	The metrics on only two of the three (a & b, a & c, b & c) against benchmarks have been satisfactory.
	9.4	Some departments or schools' metrics on all three of these (a, b & c) metrics against benchmarks have been satisfactory.
	9.5	The metrics against benchmarks on all three aspects (a, b & c) have been satisfactory across the university.

	10	**What is the extent to which there is a standard process for monitoring and taking (corrective) action where students' performance is below set benchmarks?**
	10.1	There is no agreed standard process for review and monitoring of students' performance against benchmarks.
	10.2	The university is considering developing a standard process for reviewing and monitoring student performance.
	10.3	Some indirect form of review and monitoring of students’ performance against benchmarks exist.
	10.4	Each department (or school) has its own process for monitoring and taking action on poor student performance against benchmarks.
	10.5	There is a university-wide standard process for review and monitoring of students' performance against benchmarks.

B.2 Infrastructure Assessment Questions

2: Infrastructure		
	Level	
2: Infrastructure	**1**	**What is the extent to which you have implemented a Virtual Learning Environment (VLE) platform?**
	1.1	The university has not implemented any Virtual Learning Environment platform
	1.2	We are considering implementing a Virtual Learning Environment platform (still considering other factors).
	1.3	We are in the process of implementing a Virtual Learning Environment platform.
	1.4	Some departments/schools (not all the departments) have implemented a Virtual Learning Environment platform
	1.5	The university has implemented a Virtual Learning Environment platform.
		What is the extent to which the different components of the Virtual Learning Environment (i.e. curriculum mapping, student tracking, online support for both teacher and student, electronic communication and internet links to outside curriculum resources) have been implemented or are functional?
	2.1	The Virtual Learning Environment has not been implemented (yet).
	2.2	The university is considering the implementation of the components of the Virtual Learning Environment in phases.
	2.3	Some components of the Virtual Learning Environment are already functional throughout the university.
	2.4	Some departments (or schools) have all components of the Virtual Learning Environment functional.
	2.5	All aspects of the Virtual Learning Environment are fully functional throughout the university.
		What is the extent to which the Virtual Learning Environment supports appropriate access to different e-learning information available across the university to all users?
	3.1	The Virtual Learning Environment does not support access to different e-learning information available across the university.
	3.2	The Virtual Learning Environment is functional but does not yet support access to e-learning information available for users across the university.
	3.3	The Virtual Learning Environment supports access for some users to different e-learning information across the university.
	3.4	Some departments/schools (not all the departments) have access to the different e-learning information across the university for all their users.

	3.5	The Virtual Learning Environment supports access to different e-learning information available across the university to all users.
		Please rate the extent to which you believe that there is sufficient support (e.g training) in place in using the Virtual Learning Environment platform?
	4.1	Poor - no support is offered on the use of the Virtual Learning Environment platform
	4.2	Fair - some support exists but this is on an adhoc basis
	4.3	Good - enough support is provided based on request.
	4.4	Very Good - support is provided on a regular basis.
	4.5	Excellent - support is exceptional, no improvement needed.
		Please rate the extent to which you believe that there is a mechanism in place to evaluate the successful performance of the Virtual Learning Environment platform?
	5.1	There is no mechanism in place to evaluate the successful implementation of the Virtual Learning Environment platform.
	5.2	The university is in the process of developing performance evaluation mechanism for the Virtual Learning Environment implementation.
	5.3	Some ad-hoc mechanisms exist to evaluate the successful performance of the Virtual Learning Environment platform.
	5.4	Some basic performance evaluation mechanism (not fully tailored to the university) are currently used
	5.5	Key performance indicators are used to evaluate the successful performance of the Virtual Learning Environment.
	6	**What is the extent to which you believe the institution has implemented learning analytics?**
	6.1	The institution has not implemented any form of learning analytics.
	6.2	The university is considering implementing learning analytics.
	6.3	Learning analytics software has been implemented but is not fully functional.
	6.4	Some departments (or schools) have fully functional learning analytics software.
	6.5	The university has fully implemented learning analytics software.
	7	**What is the extent to which you believe the learning analytics software (e.g. SEAtS, Student Success System) has been integrated within the Virtual Learning Environment?**
	7.1	The learning analytics software has not been integrated within the Virtual Learning Environment

	7.2	The university is considering integrating the learning analytics software within the Virtual Learning Environment.
	7.3	Some components of the learning analytics software has been integrated within the Virtual Learning Environment.
	7.4	Some departments (or schools) have fully integrated the learning analytics software within their Virtual Learning Environment.
	7.5	The learning analytics software is fully integrated within the Virtual Learning Environment
	8	**What is the extent to which you believe the different aspects of learning analytics (e.g. student retention, dashboards, at-risk detection, VLE engagement, etc) have been implemented?**
	8.1	No aspect of learning analytics is being used.
	8.2	The university is considering using some of the learning analytics elements.
	8.3	Some of the learning analytics aspects/elements are fully functional.
	8.4	Some departments (or schools) in the university have implemented all aspects of learning analytics.
	8.5	All aspects of learning analytics are currently being used in the university.
	9	**What is the extent to which there is a specific team or department (with required technical or specialised skills) in charge of learning analytics?**
	9.1	There is no specific team (or department) in charge of learning analytics.
	9.2	The university is considering establishing a department or team to be in charge of learning analytics.
	9.3	An ad-hoc team exist to support the implementation of learning analytics.
	9.4	Some departments (or schools) have dedicated teams in charge of their learning analytics.
	9.5	There is a department (or team) in charge of learning analytics within the university.
	10	**What is the extent to which you consider your institution to have the required technological infrastructure to support learning analytics implementation?**
	10.1	The institution has no technological infrastructure to support learning analytics implementation.
	10.2	The institution is building capacity of its technological infrastructure in order to support learning analytics.
	10.3	Only some aspects of the existing infrastructure can support learning analytics implementation.
	10.4	Some departments (or schools) have developed technological infrastructure to fully support learning analytics.

	10.5	The university has the required technological infrastructure to support learning analytics implementation.

B.3 Data Assessment Questions

3: Data		
	Level	
3: Data	**1**	**Please rate the extent to which you believe there was analysis of data from the Virtual Learning Environment before implementation of learning analytics**
	1.1	There was no analysis of data before implementation of learning analytics.
	1.2	There were plans to start analysing data from the Virtual Learning Environment before implementation of learning analytics.
	1.3	Some ad-hoc analysis of data from the Virtual Learning Environment was being done before implementation of learning analytics.
	1.4	Some departments (or schools) were analysing data from the Virtual Learning Environment before implementing learning analytics.
	1.5	Full analysis of data was being done before the implementation of learning analytics.
	2	**What is the extent to which data on student experience (i.e. student numbers, engagement, satisfaction, performance) is captured by the Virtual Learning Environment?**
	2.1	No data was being captured on student experience (student satisfaction, engagement, performance, attendance etc)
	2.2	There were plans to start capturing data on students' experiences (i.e. engagement, performance, satisfaction, attendance etc)
	2.3	Some basic data on students' experience (e.g. numbers, engagement, performance) was being captured by the Virtual Learning Environment.
	2.4	Some department (or schools) were fully capturing all student related data (numbers, engagement, performance, satisfaction, attendance etc).
	2.5	The university has been fully capturing data on student experience through the Virtual Learning Experience.
	3	**(Answer only if learning analytics is in place) What is the extent to which you believe that there has been significant new data captured that is accessible to you after implementation of learning analytics software?**
	3.1	No additional data is captured and accessible.
	3.2	Consideration to capture new significant data is still in the process.
	3.3	Some minor data changes (e.g. performance) are now captured and accessible.
	3.4	Some significant changes in new data captured are now accessible.
	3.5	Significant amount of new data has been provided by the learning analytics software.

	4	**(Answer only if learning analytics is in place) What is the extent to which there is regular review of reports generated by the learning analytics software?**
	4.1	No review of learning analytics reports is conducted.
	4.2	A consideration of implementing a university-wide approach to review learning analytics is being made.
	4.3	There is some review, on an adhoc basis, of reports generated from the learning analytics software.
	4.4	Some departments (or schools) regularly review reports from the learning analytics software.
	4.5	There is university-wide regular review of reports generated from the learning analytics software.
	5	**(Answer only if learning analytics is in place) What is the extent to which you believe the implementation of learning analytics has improved student engagement?**
	5.1	Student engagement has not improved after implementation of learning analytics.
	5.2	It’s not direct (clear) whether student engagement has improved after implementation of learning analytics.
	5.3	Some aspects of student engagements have improved after implementing learning analytics.
	5.4	Some departments (or schools) have recorded improvements in student engagement after implementing learning analytics.
	5.5	Student engagement has improved after the implementation of learning analytics.
	6	**(Answer only if learning analytics is in place) What is the extent to which you believe that the implementation of learning analytics has improved student retention?**
	6.1	Student retention has not improved after implementation of learning analytics.
	6.2	It’s not direct (clear) whether student retention has improved after implementation of learning analytics.
	6.3	Some aspects of student retention have improved after implementing learning analytics.
	6.4	Some departments (or schools) have recorded improvements in student retention after implementing learning analytics.
	6.5	The university wide student retention has improved after the implementation of learning analytics.
	7	**(Answer only if learning analytics is in place) What is the extent to which student performance is compared with student engagement and satisfaction?**

	7.1	There is no comparison of student performance with student engagement and satisfaction.
	7.2	Data on student performance is there but data on student engagement and satisfaction is largely unavailable.
	7.3	Some ad-hoc (irregular) comparison of student performance to student engagement and satisfaction is usually conducted.
	7.4	Some departments (or schools) make regular comparison of student performance with student engagement and satisfaction.
	7.5	There is university-wide comparison of student performance with student engagement and satisfaction metrics.
	8	**(Answer only if learning analytics is in place) What is the extent to which academic staff training needs are identified through results from learning analytics?**
	8.1	Academic staff training needs are not identified through the learning analytics platform.
	8.2	The university is considering implementing learning analytics that can also identify academic staff training needs.
	8.3	Some training needs are identified through the results from the learning analytics.
	8.4	Most of the academic staffs' training needs are identified through the results from the implemented learning analytics.
	8.5	Academic staff training needs are identified through the learning analytics integrated in the Virtual Learning Environment.
	9	**(Answer only if learning analytics is in place) What is the extent to which there is monitoring of academic staff engagement with the learning analytics in improving student experience?**
	9.1	There is no monitoring of academic staff engagement with learning analytics to improve student experience.
	9.2	The university is considering implementing a monitoring mechanism of academic staff engagement with learning analytics to improve students experience.
	9.3	Monitoring of academic staff engagement with the learning analytics in improving student experience is done on an adhoc basis (no specific guidelines).
	9.4	Monitoring of academic staff engagement with the learning analytics in improving student experience varies across department/schools.
	9.5	There is monitoring of academic staff engagement with learning analytics in improving student experience across the university.

	10	**(Answer only if learning analytics is in place) What is the extent to which there is an ethical policy governing the utilisation of student data in learning analytics?**
	10.1	There is no ethical policy governing the utilisation of student data in learning analytics.
	10.2	The university is considering developing an ethical policy governing the utilisation of student data.
	10.3	The ethical policy on utilisation of student data has not fully been adopted across the university.
	10.4	Each department (or school) has autonomy on which ethical policy to follow.
	10.5	There is a university ethical policy governing the utilisation of student data in learning analytics.

B.4 Human Resource and Skills Assessment Questions

4: Human resources and skills		
	Level	
4: Human resources and skills	**1**	**What is the extent to which training is available for both staff and students on the use of the Virtual Learning Environment?**
	1.1	There is no training available to staff and students on the use of Virtual Learning Environment.
	1.2	Training is rarely provided to staff and students on the use of the Virtual Learning Environment.
	1.3	Training is sometimes provided to staff and students on the use of Virtual Learning Environment.
	1.4	Regular training is often provided to staff but occasionally to students on the use of the Virtual Learning Environment.
	1.5	Training is readily available for both staff and students on the use of the Virtual Learning Environment.
	2	**What is the extent to which there is a dedicated team or department that gives technical support on the use of the Virtual Learning Environment?**
	2.1	There is no dedicated team (or department) to give technical support on the use of the Virtual Learning Environment
	2.2	Technical support on the use of the Virtual Learning Environment is rarely provided.
	2.3	Technical support on the use of the Virtual Learning Environment is not provided by a specific team (department), but on an adhoc basis.
	2.4	Some departments (or schools) have allocated teams to give technical support on the use of the Virtual Learning Environment.
	2.5	The university has a team (or department) dedicated to giving technical support to users (staff and students) on the use of the Virtual Learning Environment.
	3	**What is the extent to which you believe the Virtual Learning Environment team or department has sufficient staff with technical skills (e.g. data analysis)?**
	3.1	No - the Virtual Learning Environment team (or department) does not have adequate capacity (no staff with appropriate data management and data analysis skills).
	3.2	The Virtual Learning Environment team (or department) is poorly staffed (very few staff with data management and data analysis skills).
	3.3	The Virtual Learning Environment team (or department) is sufficiently staffed but in need of further training to develop data management and data analysis skills.

	3.4	The Virtual Learning Environment team (or department) is sufficiently staffed with some staff having data management and data analysis skills.
	3.5	Yes - the Virtual Learning Environment team (or department) has adequate capacity (staff with data management and data analysis skills).
	4	**What is the extent to which you have a process in place for the identification of academic staffs' training needs on the Virtual Learning Environment?**
	4.1	There is no process in place for the identification of academic staffs' training needs on the Virtual Learning Environment.
	4.2	A plan to develop a university-wide process for the identification of academic staffs' training needs is in place but has not been implemented.
	4.3	Academic staffs' training needs on the Virtual Learning Environment are identified on an adhoc basis.
	4.4	Departments (schools) have their own processes for the identification of academic staffs' training needs on the Virtual Learning Environment.
	4.5	There is a university wide adopted process in place for the identification of academic staffs training needs on the Virtual Learning Environment.
	5	**What is the extent to which you believe your institution has a technology supportive culture? (Is your institution technologically competent or is there willingness to invest appropriately in educational technology?)**
	5.1	There is a lot of resistance to any technological change across the university.
	5.2	There is some resistance to technological changes which can take long to overcome.
	5.3	There is less resistance to technological change with sufficient support from management.
	5.4	Technology change is easily accepted when implemented at departmental (school) level only.
	5.5	There is a technological supportive culture across the university where staff (and students) easily embrace educational technological change.
	6	**What is the extent to which you believe that your institution has invested in technical skills to specifically support learning analytics implementation?**
	6.1	The university has not invested in technical skills development for learning analytics implementation.
	6.2	Technical skills required for learning analytics implementation have been identified but no formal development plan.
	6.3	Technical skills development to support learning analytics is done on an adhoc basis.

	6.4	Some departments (or schools) have comprehensive technical skills development plans to support learning analytics implementation.
	6.5	There is a university-wide capacity building plan to improve technical skills that support learning analytics implementation.
	7	**What is the extent to which you believe the need for learning analytics implementation to support student learning is championed by top management?**
	7.1	No top management commitment (or support) is evident in learning analytics implementation.
	7.2	There is consideration for top management commitment to enhance student learning through learning analytics.
	7.3	Top management support to implement learning analytics to enhance student learning has to be explicitly requested.
	7.4	There is commitment from some departmental (or school) heads to support student learning through learning analytics.
	7.5	There is top management support across the university to enhance student learning through learning analytics implementation.
	8	**What is the extent to which learning analytics has been used to improve academic staff engagement with students?**
	8.1	No - learning analytics has not been used to improve academic staff engagement with students
	8.2	Consideration to use learning analytics results to improve academic staff engagement with students has been made.
	8.3	There is adhoc reference to learning analytics results in improving academic staff engagement with students.
	8.4	Some departments (or schools) have fully used learning analytics results to improve academic staff engagement with students.
	8.5	Yes - learning analytics has helped to improve academic staff engagement with students across the university.
	9	**What is the extent to which there is an effective communication process of the learning analytics results to all affected sections/departments of the institution?**
	9.1	No communication of learning analytics results is done.
	9.2	A communication process for learning analytics results is under consideration.
	9.3	Communication of learning analytics results is on an adhoc basis (i.e. only when enquired)
	9.4	Some departments (or schools) regularly communicate their learning analytics results to affected parties (i.e. staff and students)

	9.5	Results of learning analytics are communicated regularly to all relevant departments of the university.
	10	**What is the extent to which there is a regular review (or monitoring) of institutional performance (e.g. on student engagement, retention, satisfaction) based on the learning analytics results?**
	10.1	No review or monitoring of institutional performance is done based on learning analytics results.
	10.2	A consideration of implementing a university-wide monitoring mechanism of performance is being made.
	10.3	Monitoring of institutional performance based on learning analytics is carried out on an adhoc basis (irregularly).
	10.4	Some departments (or schools) regularly monitor and review their performance based on the learning analytics results.
	10.5	There is a university-wide regular monitoring and review of performance based on the learning analytics results.

Appendix C Participant Information Sheet and Consent Forms

This appendix presents the participant information sheets and consent forms for the field study phase and framework validation stage.

C.1 Field study phase

This is a briefing sheet provided to the interview participants during the field study.

Briefing Sheet and Consent Form

Project Title: Framework to Assess the Maturity Level of Learning Analytics in Higher Education and Drive Learning Services Improvement

Background Information

You are invited to take part in this research study because you constitute the key educational stakeholders in the use of virtual learning environment in higher education institutions. Your participation in this study will be to take part in a structured interview.

The purpose of this interview is to identify the current use of the virtual learning environment (VLE) at your institution and understand whether and how learning analytics (LA) is/could be implemented. Essentially, the researcher is undertaking a study to examine the levels of LA use and maturity. The aim is to improve learning services in higher education. Therefore, the information collected through the interviews will help design a framework that guides further utilisation of LA in higher education in order to improve learning services.

All information collected is used for sole academic purposes and to enrich the research. Anonymity and security of collected data is maintained throughout the research project and in accordance with the General Data Protection Regulation (GDPR). Access to the raw data will be granted to authorised individuals. This includes the researcher and a few others deemed necessary, such as the supervisory team at Cranfield University. Published work based on the study will use aggregated results and will not be linked back to any interviewee. Any publication based on the collected data from these interviews will be made available to the interviewee.

Consent

I understand that I am free to withdraw from this project at any stage during the session simply by informing a member of the research team, for whom contact details have been provided. I also understand that I can also withdraw my data for a period of up to 7 days from today, as after this time it will not be possible to identify my individual data from the aggregated results.

I confirm that I have read and completely and fully understand the information provided on this form and therefore give my consent to taking part in this research.

Signature: ___________________________

Full name: ___________________________

Contact number: ______________________

Email address: _______________________

Date: ____________________________

C.2 Case study validation phase

This is a briefing sheet provided to the validation participants. The participant information sheet was given to validation participants at PAAET and Cranfield University before the structured interviews to complete the performance measurement tool.

C.2.1 Participant Information Sheet

Participant Information Sheet

Project Title: Framework to Assess the Maturity Level of Learning Analytics in Higher Education and Drive Learning Services Improvement

You are invited to take part in this research study. This information sheet briefly outlines why the research is being done and what will be involved.

1. **Purpose of the study**

I am a PhD student at Cranfield University, Bedford, England, supervised by Dr Christos Emmanouilidis and Dr Ahmed Al-Ashaab. My research aims to develop a framework that can be utilised to assess the maturity level of learning analytics in virtual learning environments in higher education institutions and contribute to learning services improvements.

2. **Selection of participants**

You have been chosen to take part in this research project because you constitute the key educational stakeholders of learning analytics in virtual learning environment in higher education institutions.

3. **Participant involvement**

Your involvement in the study would be to take part in a structured interview where we discuss implementation of learning analytics in your education institution based on a developed performance measurement tool that is part of the maturity level framework for learning analytics in virtual learning environment. The performance measurement tool covers aspects of process, data, infrastructure and human resources that are integral to learning analytics implementation.

The interview will probably last between 45 minutes to 1½ hours depending on how much time you have available, and how much information you wish to share beyond the standard questions. As this is a structured interview with predetermined questions and answers, I will score the answers to the questions from the performance measurement tool.

If you do decide to take part, you will be asked to sign a consent form and provided with a copy of this information sheet. You are still free to withdraw from the study at any time and without a given reason.

4. Confirmation of participation

If you decide to take part in this study, please reply affirmatively to the email sent to you requesting for your participation. Email address: ab.alenezi@cranfield.ac.uk

Or a verbal confirmation to the telephone conversation made soliciting for your participation. You can call the researcher on +447490 000082

I will explain what the research is about and can also answer any questions you might have. When you have decided to go ahead with the interview, we can arrange a suitable time and location.

5. Confidentiality and anonymity

All information that is collected during the course of the research will be kept strictly confidential.

Your name or any contact details will not be recorded on the interview transcripts. In addition, any details which potentially could identify you will also be removed or changed. My academic supervisors will have access to the anonymised transcripts of your structured interview, but I will be the only person to have access to the original interview, your consent form and any of your contact details. Your participation in this study will not be discussed with other interviewees. Also, your name will not be mentioned in the research as I will use anonymised quotes in all publications.

6. Usage of research results

The results of the study will be used in my PhD thesis. The material will be presented at academic and professional conferences and in academic journals.

Anonymity and confidentiality will be upheld in all cases. Findings from this study will contribute to effective implementation of learning analytics in virtual learning environment in higher education institutions in order to improve learning services.

7. Funding of the project

The PhD programme, for which this project is undertaken, is funded by the Government of the State of Kuwait.

8. Contact for further information

Abdullah Alenezi
Telephone: +447490 000082
Email: ab.alenezi@cranfield.ac.uk

C.2.2 Consent Form

Consent Form

Full title of Project: Framework to Assess the Maturity Level of Learning Analytics in Higher Education and Drive Learning Services Improvement

Name, position and contact address of Researcher:
Abdullah Alenezi
PhD Student
School of Aerospace, Transport and Manufacturing
Cranfield University
Bedford
MK43 0AL
United Kingdom

Email: ab.alenezi@cranfield.ac.uk
Mobile: +447490 000082

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

Name of Participant: Date:

Position: Signature:

Appendix D Kuwait Economic and Economic Context

This appendix provides additional context about the country Kuwait, supplementing the discussion in section 3.3. The geographical, economic and governance contexts are presented in appendix D.1, D.2 and D.3 respectively.

D.1 Geographic location of Kuwait

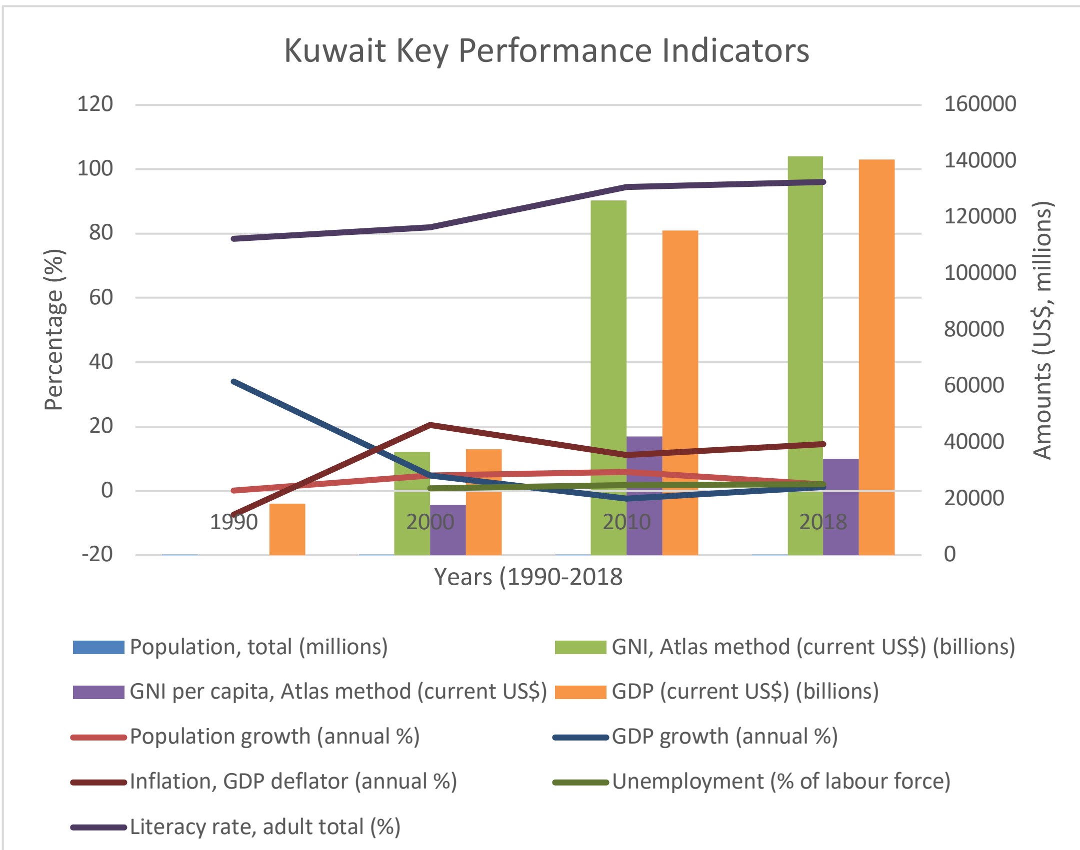
Kuwait is located in the Middle East, bordering the Persian Gulf, between Iraq and Saudi Arabia. See figure below.

Source: World Atlas, 2020

Figure 8-1: Geographical location of Kuwait

D.2 Kuwait World Governance Indicators

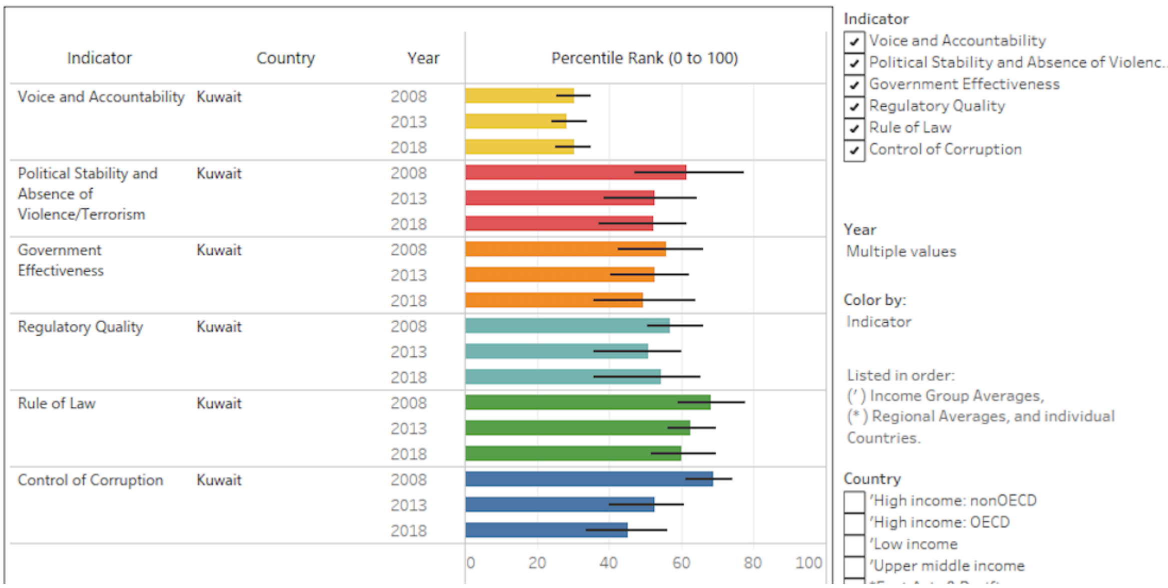
Some key performance indicators of Kuwait are shown in figure below over the period 1990 to 2018. Data has been collected for GDP (amount and percentage change) population (number and percentage change), GNI and GNI per capita, unemployment, inflation and literacy rate sources from the World Bank database.



Source: Data from World Bank Database

Figure 8-2: Key Performance Indicators for Kuwait

The figure below shows the world governance indicators for Kuwait. This captures country governance indicators on six dimensions: voice and accountability, political stability and absence of violence, governance effectiveness, regulatory quality, rule of law and control of corruption (Worldwide Governance Indicators, 2020).



Source: Kaufmann et al., 2010; Worldwide Governance Indicators, 2020

Figure 8-3: World Governance Indicators