Student retention and learning analytics: a snapshot of Australian practices and a framework for advancement

Final Report 2016

University of South Australia

The University of Melbourne

University of Technology Sydney

Macquarie University

University of the Sunshine Coast

University of New England

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List of acronyms used

ALASI	Australian Learning Analytics Summer Institute
ASCILITE	Australian Society for Computers in Learning in Tertiary Education
DVC	Deputy Vice-Chancellor
ECAR	Educause Centre for Analysis and Research
EDM	Educational Data Mining
EDW	Enterprise Data Warehouse
HERDSA	Higher Education Research and Development Society of Australasia
ICT	Information and Communication Technologies
LA	Learning Analytics
LAK	Learning Analytics and Knowledge Conference
LASI	Learning Analytics Summer Institute
LMS	Learning Management System
OLT	Office for Learning and Teaching (Australian Government)
PVC	Pro Vice-Chancellor
SOLAR	Society for Learning Analytics Research
SIS	Student Information System
UA	Universities Australia
VET	Vocational Education and Training
VC	Vice-Chancellor

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Executive Summary

The analysis of data from user interactions with technologies is changing how organisations function, prioritise and compete in an international market. All industries have been influenced or impacted by the so-called digital revolution and the associated analysis of user data. In the higher education (HE) sector this wave of data analytics has flowed through to the concept of learning analytics (LA). This field of research has been touted as a game changer for education whereby the outcomes of LA implementations will address core education challenges. These include concerns regarding student retention and academic performance, demonstration of learning and teaching quality, and developing models of personalised and adaptive learning. While there is broad consensus across the sector as to the importance for LA there remain challenges in how such endeavours are effectively and efficiently rolled out across an organisation. The lack of institutional exemplars and resources that can guide implementation and build institutional capacity represents a significant barrier for systemic adoption.

This report seeks to unpack these challenges to institutional adoption and provide new insights that can aid future implementations of LA and help advance the sophistication of such deployments. The study does so by interrogating the assumptions underpinning the adoption of LA in the Australian University sector and contrasting this with the perspectives of an international panel of LA experts. The findings and recommendations highlight the need for a greater understanding of the field of LA including the diversity of LA research and learning and teaching applications, alongside the promotion of capacity building initiatives and collaborations amongst universities, government bodies and industry.

Approach

This report comprises two separate yet complementary studies. The first study (Study 1) involved the analysis of qualitative interviews with senior leaders about LA implementations that were occurring in their respective institutions, and perceived affordances and constraints. It was concerned with eliciting insight into current implementations, and the processes and drivers that shape them. The coding framework applied to the interview data afforded opportunity for further cluster analyses. The cluster analysis revealed the complexity and multidimensionality of LA projects as well as the emergence of two distinct implementation profiles.

Study 2 builds on this earlier work by investigating the factors perceived as necessary for establishing sustainable LA implementations that demonstrate long term impact. Owing to the relatively nascent status of LA within the higher education sector, it was not possible to elicit such insight from the examination of extant programs. Therefore a concept mapping exercise was developed that solicited opinion and insight about future requirements, from an international panel of expert practitioners, researchers and stakeholders.

Findings

The findings from Study 1 revealed two distinct trajectories for institutional LA implementations. Universities within the first cluster largely identified LA as a process to address student retention. Institutions in cluster 1 therefore, tended to adopt a solution focused model for deploying LA. In practice, this model of implementation was framed around a technical solution and the provision of data to prompt action from teachers. Project management was hierarchical with few cross-organisation stakeholders. In contrast, the second trajectory (cluster 2) viewed LA as a process to bring understanding to learning and teaching practices. The models of implementation were more complex than cluster 1 and involved a greater diversity of stakeholders. Typically, for cluster 2, LA was viewed as a site for potential disruption and innovation to improve the quality of the student learning experience. The first study illustrates the intertwined and somewhat contested relationships that underpin the dimensions comprising the two clusters (e.g. leadership, strategy, readiness, conceptualisation, technology). Collectively, these dimensions inform how senior leaders respond to institutional challenges, enable leadership and define learning analytics and thereby how an organisation sets in motion its deployment, project management, and scope of its LA endeavours. We term this collective as the institution's strategic capability.

The results from the international expert panel in Study 2 identified a seven cluster solution of the dimensions that lead to long term sustainability of LA. The panel noted that the establishment of a strategic vision that is sensitive and responsive to the needs of the organisation is critical for long term impact. Also prominent in the model was the need to engage with multiple and diverse stakeholders, to build capacity and innovation, and to ensure that technical and data affordances are robust, transparent, reliable and practical. Other dimensions related to the need for student empowerment in LA.

The findings from the two studies suggest that sustainable LA adoptions consist of a number of mutually influencing affordances and constraints within a complex system. To represent this we draw on the field of system dynamics [71] to illustrate the way resources (stocks) 'flow' through a system to either influence or constrain outcomes. Two key capabilities for LA implementations include a strategic capability, that orchestrates the setting for LA; and an implementation capability, that integrates actionable data and tools with educator practices. These capabilities are essential drivers that push/pull educator uptake of LA from 'interested' to 'implementing'. The findings suggest two additional drivers. First, implementers require an analytic tool or combination of tools that manage data inputs and generate outputs in the form of actionable feedback. The capacity to implement is crucially linked to the quality of these tools and the data they rely on and generate. Second, this in turn requires an organisational learning capacity to monitor implementations and improve the quality of the tools, the identification and extraction of the underlying data, and the ease and usability of the feedback interface. As these increasingly meet the "real" needs of learners and educators, organisational uptake is accelerated. Thus, the elements identified have the potential to act in concert to form a reinforcing feedback loop. Figure 1 presents the flow of resources (stocks) in this system, their influence on each other, and the major reinforcing feedback effect.

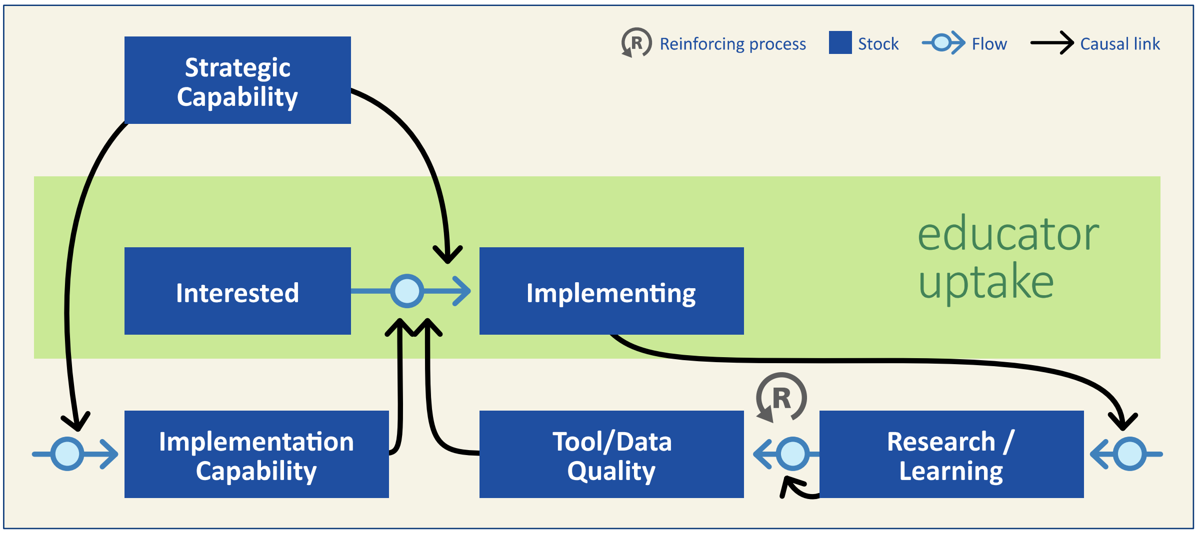

Figure 1. Model of system conditions for sustainable uptake of LA

Recommendations

This report provides insight into current LA implementations and the array of mediating conceptual and structural factors that are shaping how LA is utilised. Overall, there is much interest in LA and the field clearly has much potential to help shape the future of education. However, at present LA projects across Australian universities are, in the majority, immature and small in scale. The report identifies areas that require further consideration and support if LA is to provide long term and meaningful impact for the education sector. These include:

- Facilitating broader institutional, cross institutional and government discussions of LA and its capacity to inform sectorial challenges.
- Developing capacity building initiatives. This may manifest as professional development, secondments, and postgraduate course opportunities.
- Developing and supporting new models of education leadership that embrace complexity and enables innovation, organizational agility and adaptivity.

The relative silence afforded to ethics across the studies is significant. The lack of discussion does not reflect the seriousness with which the sector should consider these issues. Internationally, there has been significant investment devoted to the development of resources that can guide institutions through the many ethical implications and challenges that LA will surface. Given the nascent status of LA in the Australian context there has not been a pressing need to undertake such conversations. However, as LA projects mature, ethical considerations will take on a heightened salience. It is recommended that a national conversation be initiated in which ethical considerations will be identified, framed and possible actions identified.

Chapter 1

1.1 Introduction

Learning analytics (LA) has been heralded as a ‘game changer’ for higher education [1]. Despite the relative infancy of this research field many commentators have noted the vast potential of LA for improving the quality of teaching and addressing challenges related to student retention and personalised and adaptive learning. Statements range from LA being the “most important educational movement of the last 100 years” [2], to the more tempered claims for analytics informing incremental improvements to learning and teaching practice [3]. However, and despite the well acknowledged promise of LA and the significant research advances made to date, institutional adoption has typically been limited in scope and scale. This clearly leads to questions regarding why institutional deployment of LA remains disjointed, hesitant and faltering?

Recently, there have been several analyses of LA implementations and their concomitant challenges [4-6]. However, there remains a dearth of empirically-informed resources that can effectively guide institutions in how to establish LA [4]. The lack of institutional exemplars and resources presents a serious impediment as the sector seeks to embed LA and build institutional capacity. Further, LA’s broad data sources and horizontal organisational implementation demands a response that is equal to its complexity. We argue that the complex nature of LA poses a challenge to many extant theories and models for organisational adoption [7-9] and suggests that simplified conceptualisations of institutional issues and challenges may be maladaptive.

This report aims to add further insight into the complexities surrounding institutional adoption of LA. The study does so by interrogating the assumptions underpinning the adoption of LA across Australian universities and contrasting this with the perspectives of an international panel of LA experts.

The report begins with a literature review providing context and definition surrounding LA. Next, the review examines previous attempts to capture models of LA implementation. While we draw on and find much value in the dimensions identified in the literature, it is nevertheless apparent the existing models often represent LA as a linear, stepwise process. In our first study we examine the degree of complexity that is associated with LA projects. Here we build a rich picture of actual and planned implementations in the Australian context, as revealed in interviews with university senior leaders. We then calibrate the current state of practice with our second study, a future-oriented concept mapping exercise with leading LA exponents on the features of a sustainable implementation. Collectively, these studies offer a unique perspective on the key capabilities required for an enduring adoption of LA, one that ensures the flexible capacity necessary to meet foreseeable demands, and demonstrates value for institutions, educators, and students. The concluding discussion elaborates on these findings, providing a set of recommendations for University leaders and the sector more broadly.

1.2 Literature Review

The growth in adoption of education technologies such as learning management systems (LMS), student information systems, social media, and lecture capture has enabled access to large stores of data related to learning and teaching practice [10, 11]. Broadly speaking, these digital traces can be 'mined' and analysed to identify patterns of learning behaviour that can inform education practice [5, 12]. This process has been described as LA [13]. The study of LA has been defined as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [13]. These forms of analyses have been demonstrated to provide detailed insight into areas such as student retention and academic achievement [14-16], self-regulated learning [17], sense of community [18], and learning dispositions [19].

LA is a bricolage of disciplines. The field has drawn heavily on other analytic domains such as business intelligence in the corporate sector, web analytics, academic analytics and educational data mining [20] to support decision making and planning in education [21]. As such, LA has evolved from multiple disciplines and established research areas and methodologies such as social network analysis; discourse analysis; machine learning; human computer interaction; learning sciences; education psychology and statistical analysis. A direct benefit of the multi-disciplinary nature of LA and the rise of cyber infrastructure and 'big data' is the ability to investigate new and old questions using new approaches. For instance, LA presents an opportunity to provide 'real-time' feedback on student learning through predictive analytics [22]; or discourse analytics [23, 24] possibly visualised through actionable analytic dashboards [25]. These forms of analytics and visualisations for feedback afford new prospects for establishing proactive and timelier interventions in support of learning and course modifications, in contrast to the more traditional post-hoc student and course evaluations [26, 27].

In the Australian context, higher education institutions are acutely conscious of, and motivated by, the consequences of student attrition, and are therefore directing resources and energy towards such retention-based initiatives [28]. A brief overview of such strategies follows.

1.2.1 Student retention and learning analytics

The sensitivity to and importance placed on retention across the sector has manifested in the emergence of numerous strategic initiatives and technologies that focus support on "at-risk students" [29, 30]. The early identification of at-risk students affords the introduction of learning supports and interventions to improve student retention. Predictive analytics are increasingly adopted to inform such interventions. These analytics typically build a student profile from a weighted combination of demographics, online engagement data (e.g. LMS activity) combined with an assessment of aptitude – commonly prior grades [14]. A 'flagship' exemplar of LA and predictive modelling lies in the work of John Campbell from Purdue University. Campbell and colleagues [11] developed the 'Course Signals' software to identify students at-risk of failure. The software provides automated prompts to promote help seeking behaviour and learning support in a proactive manner. There are numerous other examples now illustrating the potential for LA to provide powerful early alerts systems to help address student retention concerns [15, 31]. Jayaprakash et al [16] provide an extensive overview of early alert systems through predictive modelling in learning analytics.

The momentum from such research and technical work alongside the increasing imperative for institutions to focus on retention-related activity has sparked a flurry of predictive analytics commercial software and services (e.g. BlackBoard Analytics; BrightSpace Insights; Blue Canary; IBM; Civitas Learning and Cortell). A primary focus of many the commercial vendors therefore relates explicitly to the predictive modelling of student data that will aid early identification of students at-risk of academic failure. However, to date there has been limited research empirically testing the impact of such interventions on long-term retention efforts, nor critically examining how the application of predictive analytics relates to broader understandings and conceptualisations of student retention. Also, and of particular interest to this research, there is emerging literature that challenges the current, conventional conceptualisation of retention as a central, distinct construct that can be directly addressed and influenced through targeted intervention. Kahu [32] instead positions retention as a distal outcome of student engagement, a construct itself that exists within a complex, interdependent, interconnected network, including structural, pedagogical, and psychosocial antecedents, which influence proximal and distal consequences. Such a conceptualisation suggests the possibility of retention being addressed not at the point of student departure, but rather in how students engage with these antecedent elements.

This report is situated at this juncture. Its foci include better understanding how LA are currently employed in Australian institutions, how LA might look in the future, and gleaning insight into the relationship between LA and retention at conceptual and operational levels.

1.2.2 Extant frameworks of LA implementations

There is a wide range of LA implementation models and frameworks employed across the higher education sector, each affording insight into the various dimensions and factors shaping LA, and how it can be more productively operationalised. For examples, see Greller & Draschler, Norris and Baer and Davenport [5, 33-35]. However, to date, the idealised conceptualisations these models aspire to are yet to be fully realised, and LA implementations across higher education institutions are typically immature, small in scale, and with limited ability to demonstrate institutional impact [36]. Explanations for the failure of such conceptual models to translate to an implementation context are multifaceted and include temporal considerations, such as the constraint of time on the development and maturity of implementations; the complexity of both LA and the educational institution in which it is being implemented; a current scarcity of empirical validation of models, and the nature and salience of the interdependent factors and dimensions shaping LA implementations; and a divergence in conceptualisations and understanding of key constructs or dimensions of LA. The findings of this report contribute empirical insight into our understanding of these factors.

1.3 Present Study

This report is composed of two separate studies. Study 1 was concerned with eliciting empirically-informed insight into how LA implementations in Australian universities actually look, and the processes and drivers that shape them. Interviews were conducted with senior leaders about LA implementations that were occurring in their respective institutions. Qualitative analysis of interview data provided a lens through which the complexity of LA implementations could be accounted for and examined. A subsequent cluster analysis exposed relationships between antecedent factors and implementations, and revealed the relative criticality of relationships between dimensions of LA. Finally, current drivers, affordances, and implementations of actual LA initiatives were scrutinised, and data was triangulated against institutional conceptualisations of retention, providing insight into and further understanding of this important, albeit sometimes assumed, relationship.

Study 2 complements this work by investigating the required factors necessary to generate sustainable LA implementations that effectively demonstrate long term impact. Owing to the relatively nascent status of LA implementations within the higher education sector, it was not possible to elicit such insight from the examination of extant programs. Therefore a concept mapping exercise was developed that solicited opinion and insight about future requirements, from an international panel of expert institutional leaders, practitioners, and researchers.

The aims of this report include:

- Determine the current state of LA in the Australian higher education context, including insight into institutional goals, plans, preparation and implementation activity
- Determine critical relationships between institutional LA and retention initiatives
- Elicit insight into key affordances and constraints of sustainable and effective LA implementations in the higher education context.

An overview of the design of the two studies underpinning this report is captured in Figure 2**.** The two studies, including their methods and results, are then reported in turn.

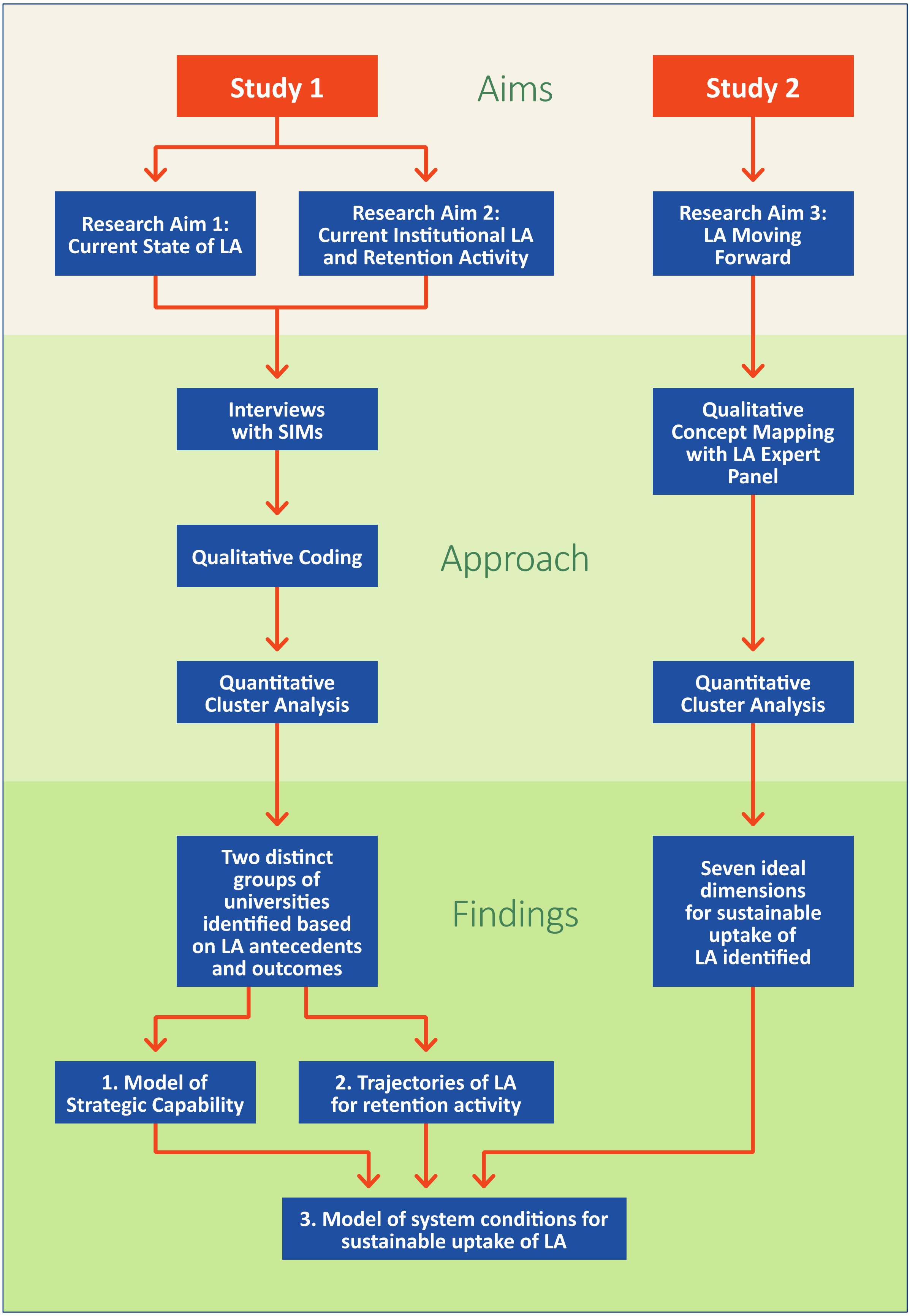

Figure 2. Overview of the research design of Study 1 (current state of the art and initiatives) and Study 2 (future sustainability)

Chapter 2 – Study 1

2.1 Objective

The primary objective for Study 1 was to understand how senior institutional leaders perceived learning analytics including the drivers, affordances and constraints that shape LA within their institutional context.

2.2 Methodology

2.2.1 Interviews

Senior institutional leaders (Deputy Vice Chancellors) across all Australian universities were invited to participate in an interview with the project team to discuss current state of LA projects. This resulted in some 32 recorded interviews with senior institutional leaders charged with responsibility for LA implementations. Themes explored in the interviews included:

1) Perceptions and understandings of LA;
2) Detail about planned or current implementations;
3) Strategy and policy developments; and
4) Resource implications and challenges.

Interviews were approximately 45 minutes in duration and utilised a flexible, semi-structured approach, employing gentle probes to elicit detail and encourage clarification of concepts, themes and ideas that surfaced. See Appendix B for a copy of the interview protocol.

2.2.2 Analysis and Coding Protocol Development

Preliminary analysis of the interview data (as outlined in Appendix C), clarified that a more nuanced coding protocol was required that was capable of illuminating the multi-dimensional, interdependent nature of factors influencing the implementation of LA. A coding protocol was developed that would highlight patterns and differences across institutions, elicit insight into how LA implementations qualitatively differed across institutions, and empirically scrutinise relationships between antecedents and outcomes of LA implementations. Utilising a mixed, integrated qualitative methodology, the coding protocol was both inductively and deductively generated (See Appendix D for full procedure). Themes that emerged were informed through analysis of participant responses in addition to theoretical concepts from the literature [37-39]. A full copy of the coding protocol can be found in Appendix S.

2.2.3 Cluster Analysis

After the coding protocol was applied to the interview data, an investigatory cluster analysis was performed (See Appendix E for cluster analysis methodology). The dimensions examined through the cluster analysis were grouped into 'Concept', 'Readiness', 'Implementation', and 'Context' categories. The grouping of dimensions into categories is presented in Appendix F, and descriptions of the categories are presented in Appendix G.

2.3 Results

Broadly speaking, all of the interviewees were positive about LA, its developments, application and potential to address institutional teaching and learning challenges. Senior leaders frequently noted the wide possibilities for LA in their institutional context and as such noted that LA was an area of strategic priority. While there was consensus regarding the potential of LA in education, the cluster analysis revealed the complexity and multidimensionality of LA implementations as well as the emergence of two distinct implementation profiles. The findings from the cluster analysis are discussed in more detail below.

2.3.1 Identification of the 2 Cluster Groups

The first stage of the cluster process involved the identification of two medoid[1] institutions. A breakdown of concept and readiness variables associated with the two medoid institutions is captured in Appendix H, and a visual representation comparing them is found in Figures 3 and 4. In Figures 3 and 4, the concept and readiness variables are arranged into columns, and levels of variables are displayed as rows. The figures map and compare the movement of medoids across the levels of variables, providing insight into the differences in experiences between the two institutions.

Through Partitioning Around Medoids (PAM) clustering, all remaining universities were allocated to either Cluster 1 or Cluster 2, such that university dissimilarity to the medoid was minimised within groups. Appendix I presents the allocation of all universities to either Cluster 1 (n=15) or Cluster 2 (n=17), and details their values across concept, readiness, and implementation variables.

[1] Medoid refers to "exemplar" data points, or representative universities (Appendix E).

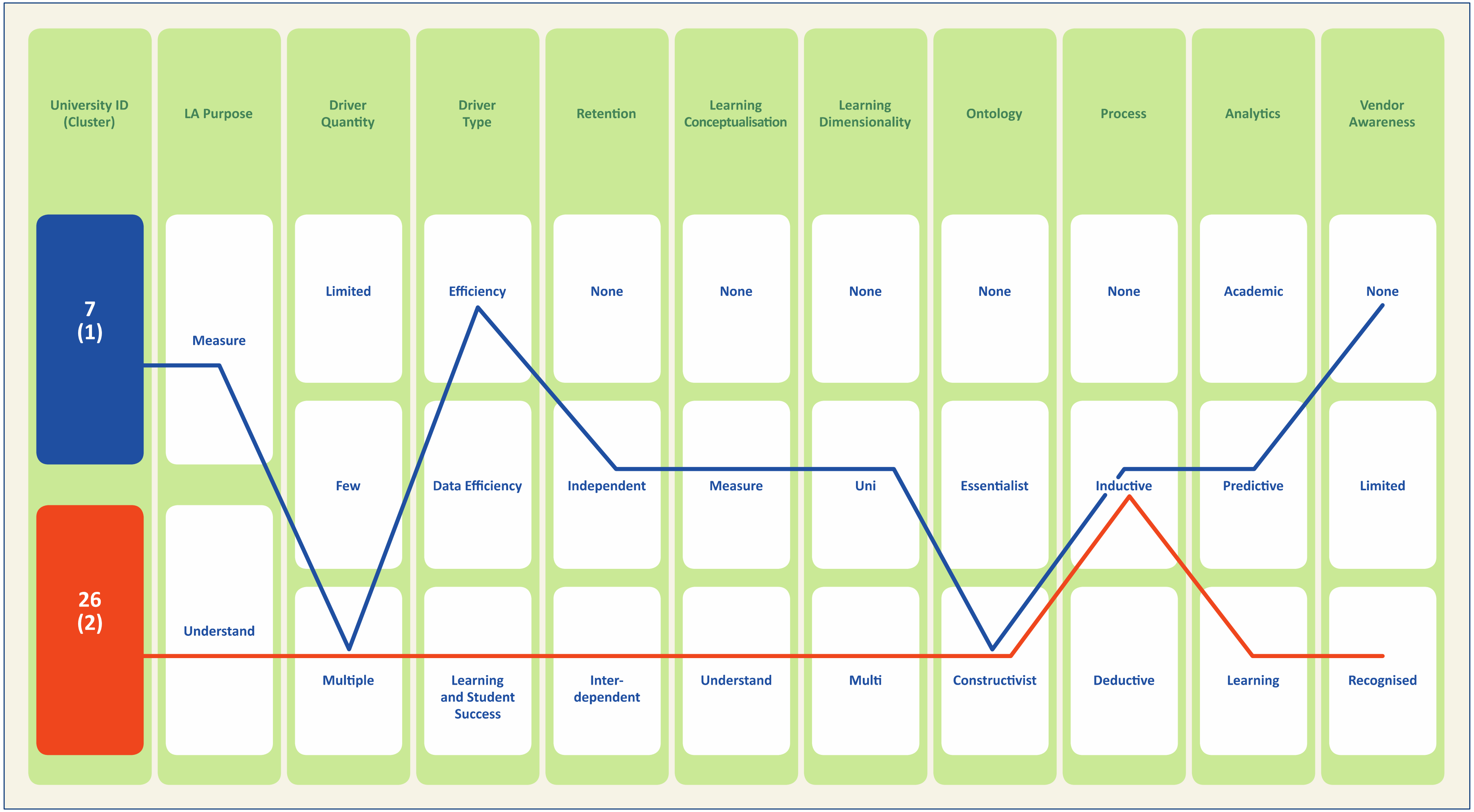

Figure 3. Visual representation of medoids across concept variables

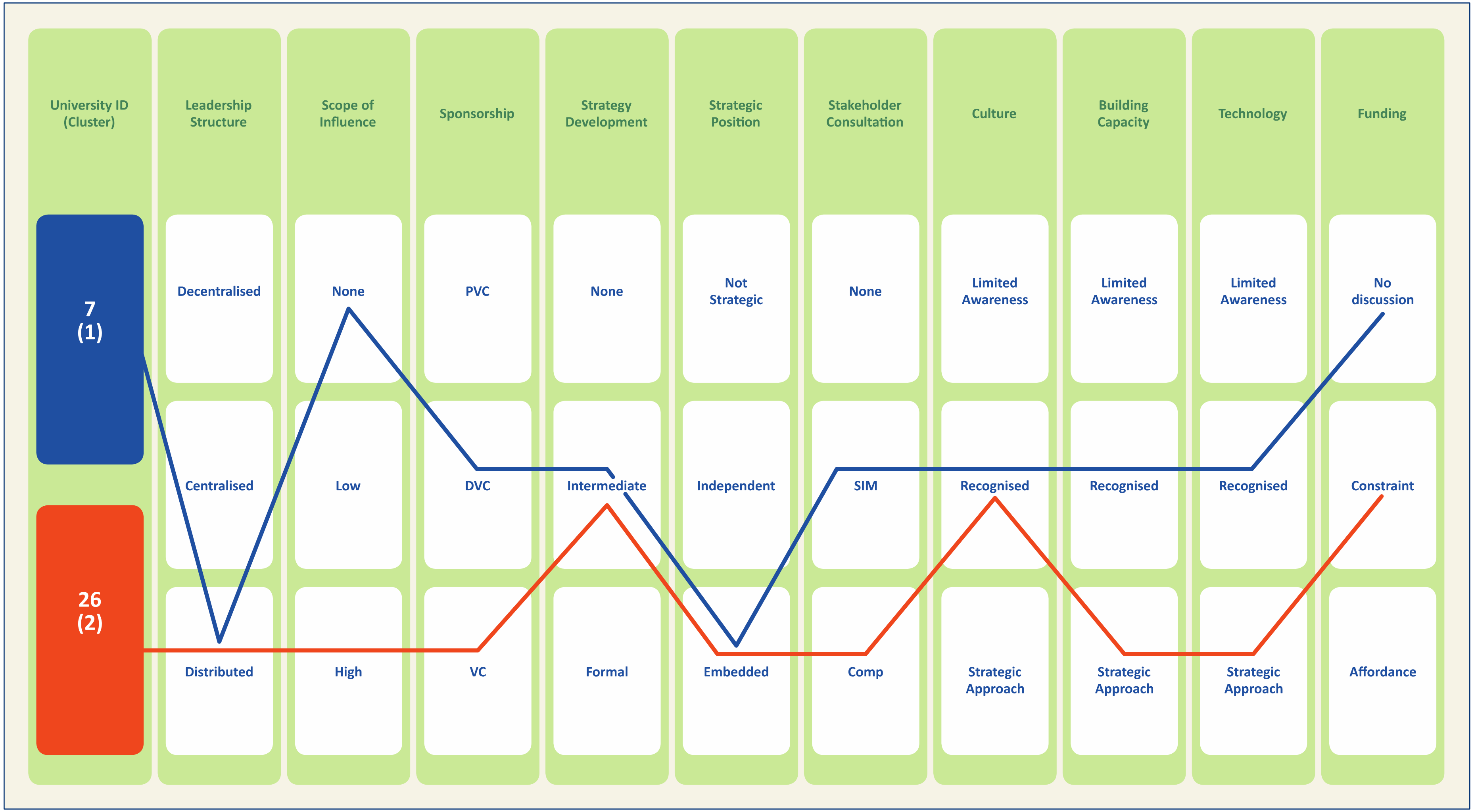

Figure 4. Visual representation of medoids across readiness variables

2.3.2 Differences between Clusters

The analysis revealed significant differences between clusters across **concept, readiness** and **implementation** variables. The occurrence of statistical difference between clusters is presented in Appendix J, and a summary table of the variables where institutions differed significantly is provided in Appendix K.

While at first it was anticipated that the clustering would expose obvious patterns in terms of implementation progress, this was not the case. Both clusters exhibited a mixture of institutions at early and preparatory stages. However, significant qualitative differences emerged across the clusters with regard to planning and preparation, and implementation focus. For instance, Cluster 1 was dominated by conceptualisations of LA as a vehicle or tool for measurement or efficiency-gains. As such, within this cluster the implementation of LA was primarily directed towards student retention activity. Retention was conceptualised as a phenomenon independent of teaching and learning activities. Cluster 1 had a higher percentage of institutions implementing LA than found in Cluster 2. However, implementations in Cluster 1 also appeared to be more targeted and focused on an institutional concern (e.g. student retention). There was minimal discussion of analytics being used to understand the student learning process and inform program and course curriculum practice. In this context, the broader applications of LA, (such as discourse analytics, social learning analytics, self-regulated learning) were overshadowed by a direct focus on student retention activity.

Within Cluster 1, readiness factors were at early stages of development, with institutions reporting no or nascent strategy development. While organisational culture and capacity were acknowledged as highly salient, very few institutions had addressed these issues at a strategic or even operational level. However, seven out of the 15 institutions in Cluster 1 had taken formal steps towards improving their technical infrastructure. These findings are also consistent with the work of West, et al [40] in noting that although LA is in early stages of development there is growing investment in technologies that will effectively support the institutional uptake of LA.

While fewer institutions in Cluster 2 were implementing LA, there was greater diversity in how analytics could be used across the institution to inform student learning. LA and learning were both represented as integrated phenomena. In contrast with Cluster 1, efficiency was typically not mentioned by Cluster 2 institutions as a driver for LA, and retention was conceptualised as a (distal) activity directly connected to antecedent teaching, learning and student experience factors. Reflections on vendor tools and products were generally more circumspect than in Cluster 1. While both cluster groups reported the utilisation of vendor products as part of their LA implementations, the data suggested that institutions in Cluster 2 were more aware of the constraints and limitations that might be connected with their use. Cluster 2 institutions typically had significant senior leadership input and engagement with sponsorship at the VC and DVC levels. In comparison, Cluster 1 institutions primarily exhibited sponsorship across PVC and DVC levels, with few reporting VC involvement. Strategy development was typically more mature than in Cluster 1, and there was evidence of comprehensive and wide reaching stakeholder engagements. There was also evidence in Cluster 2 of developing organisational technical readiness, with 11 out of the 17 institutions strategically extending their technology capacity beyond their data warehouse.

2.3.3 Readiness Factors

Notably, with the exception of technology readiness and stakeholder engagement, other readiness factors did not emerge as significant in the cluster analysis. However, when scrutinising the 14 institutions that did not report an implemented LA program, significant patterns were observed in the data. A summary of these institutions is presented in Appendix L. Cluster 1 institutions that did not report an existing LA program were yet to address any of the readiness factors. That is, within the interview, there was an absence of discussion surrounding implemented strategies or programs that would aid awareness and organisational acceptance, or to develop organisational capacity. In comparison, in Cluster 2 readiness factors were in place. This was consistent even for those institutions that were yet to fully implement an LA program. In essence, communication, human resource and development processes and systems were in place for the commencement of implementation initiatives. These data remind us of the importance of such readiness dimensions, especially in the formative stages of LA implementation. The bifurcation of findings across the two Cluster groups suggests that even in nascent stages of LA implementation, conceptualisation of key LA and retention constructs are mediating how institutions proceed with their LA implementations.

2.3.4 Retention

Across the two cluster groups, the primary driver for LA was student retention initiatives. However, and again, two distinct patterns emerged between how institutions conceptualised retention, and how they operationalised LA to inform retention initiatives. In Cluster 1 there was a strong understanding of retention as a (reified) phenomenon independent from other antecedent factors, notably teaching and learning. Cluster 1 implementations appeared to reinforce this understanding, with no institutions in this cluster group reporting planning or preparation that would suggest extending the application of LA into other learning and teaching domains. The prediction of students at-risk early in their academic candidature was the key task for LA operations. This process was perceived to afford opportunity to provide timely interventions and support. By contrast, Cluster 2 institutions predominantly constructed retention as an activity distally connected to a student's broader social and academic experiences. While there was still a strong focus on LA as a tool to aid retention, a number of institutions in Cluster 2 reported that a goal of LA was to develop insight into improving student learning outcomes.

2.3.5 Context

The study also aimed to identify the broader contextual factors that may influence institutional implementation of LA. For this purpose context included an institution's retention rate, student success rate, size (student numbers), category of institution (if any), and location (State, rural, regional or city based). While the findings from the cluster analysis suggest that the relationship between these contextual features and LA outcomes was not significant, there appeared some associations that are worthy of further investigation. The lack of significance in this case may be due to the small sample size. The data revealed that eight out of the ten universities with the lowest retention outcomes, and seven out of the ten with poorest student success outcomes were associated with Cluster 1. In contrast, Cluster 2 contained a greater number of institutions (7/10) with higher retention rates (in comparison to Cluster 1). A similar association was observed in relation to success. Eight out of the top ten institutions ranked by student success were located in Cluster 2. Seven out of the ten of the largest universities were also in Cluster 2. Although no statistical significance emerged in the present study, it is suggested that further investigations involving a larger sample size are undertaken to examine the impact of contextual dimensions on LA implementations.

2.3.6 Summary

The findings from Study 1 indicate there are two distinct 'trajectories' of LA implementation demonstrated in Appendix H and Figures 2 and 3. One trajectory is focused on measurement and broader performativity precepts and retention interventions. The second trajectory is underpinned by pursuit of understanding, with an emphasis on learning, and recognition that retention is consequential to broader teaching, learning and engagement experiences for students. The importance of informed and committed leadership was reinforced. Relationships were observed between the level of perceived senior leadership engagement and implementation of LA projects. While leadership has been frequently cited as a key mediating dimension in LA implementation, limited work has empirically scrutinised and compared the processes underpinning, and efficacy of, different leadership styles as they relate to LA outcomes.

The findings suggest that LA implementations and initiatives are a product of more than the 'readiness' factors (operationalised in this study as leadership, strategy, organisational culture, organisational capacity and technology) often cited in the literature. Rather, it appears that readiness factors are in turn tempered, if not mediated, by the broader constructions and understandings that leadership had about LA, and its perceived benefits and potentialities. Importantly, the data did not identify causality in the relationships across the dimensions. Instead it is possible that the three categories of variables (concept, readiness, and implementation) are recursively interconnected.

Chapter 3 - Study 2

The second phase of the research was a hybrid qualitative/quantitative investigation of the dimensions of a sustainable uptake of LA. As such, this component of the report aimed to extend beyond the Australian higher education context to examine alternate approaches. Consequently, this second investigative phase was designed to offer a future perspective that could then be used to expand on, or critique, current and planned practice. To achieve this we engaged selected members of the international LA community in a *concept mapping* exercise.

3.1 Concept Mapping

'Concept mapping' is a generic term that describes a wide range of techniques for the diagrammatic representation of ideas. There are two distinct approaches to concept mapping. One is the manual construction of visual, semantic trees or networks to express key concepts and their relationships, based on educational research such as that of Joseph Novak [41]. The other approach computes concept clusters (with no semantic relationships other than cluster membership) based on ratings of the concepts' attributes such as similarity, importance, or parent-child relationships. When conducted as a collaborative exercise, the data comes from multiple analysts. It is this approach that the study adopted. Thresholds can be adjusted to merge/split clusters, in order to discern the most meaningful patterns. There is not one single 'correct' cluster analysis: human interpretation is an integral part of the process. Essentially it is a structured process that externalises the disparate knowledge held by diverse stakeholder groups, allowing them to share and organise their conceptual understandings.

3.2 Method

3.2.1 Participants

The project team invited 79 Australian and international LA experts to participate in this phase of the investigation. The team used their knowledge of the field, derived from their extensive experience as researchers along with the experience of some of the founding members of, and holders of executive positions within, the Society for Learning Analytics Research (SoLAR), to narrow the candidate pool. Potential participants were screened according to two main criteria: they had documented expertise in LA and their peers considered them leaders. A recent citation analysis [42] was used to calibrate this selection process. In addition the panel aimed to secure representation from four distinct areas: research, implementation, senior management, and the not-for-profit advocacy agencies (e.g. Educause, JISC).

Of the 79 potential candidates 42 experts consented to participate. Thirty (30) of these subsequently accepted a formal invitation to begin the process using an online concept mapping interface managed by *Concept Systems Inc* (www.conceptsystemsglobal.com). Twenty eight (28) experts completed the brainstorming and sorting phases that were used for the cluster analysis, and 25 experts stayed the course of the investigation and also completed the rankings of the statements. The full 28 that completed the major components of the investigation are subsequently referred to as the 'expert panel'. The constitution of this final expert panel was: Researchers (n= 13), Senior Institutional Leaders (n = 9), Implementer/Practitioners (n = 3), Vendors (n = 2). No not-for-profit advocacy agency representatives completed the major components. One (1) participant did not specify a role.

3.2.2 Procedure

The procedure involved three main phases, namely – brainstorming, sorting and ranking. In the brainstorming activity the expert panel were asked to respond with as many concepts as they liked to the key phrase: *'for LA to make a continued impact on learning and teaching it would need to…'*. One hundred and sixteen (116) statements were generated in response to this prompt. These statements were then filtered by the project team to remove redundancies, leaving a total of 74 unique statements. The statements covered a broad range of LA spheres and activities (refer to Appendix M for a full list of the statements).

In the sorting phase all of the statements (74) were then re-presented to the expert panel who were asked to sort them following the instructions to "group the statements for how similar in meaning or theme they are to one another" and to give each category a name that describes its theme or contents. In addition, they were instructed not to create categories according to priority, or value, such as 'Important', or 'Hard To Do' or to create categories such as 'Miscellaneous' or 'Other' that group together dissimilar statements. The expert panel were further requested to ensure that all statements were allocated and no one individual statement was isolated to a separate category. One participant failed to follow these instructions and their sorting was thus excluded from the analyses.

Following the sorting phase the participants then ranked each of the 74 statements on both their importance and feasibility, using a 5-point Likert scale ranging from "not at all important" to "very important".

3.3 Results

After a thorough inductive analysis (outlined in and Appendices N and O), the investigators arrived at a seven cluster solution as presented in Appendix P, and summarised in the following section. Appendix Q details the clusters with examples of their constitutive statements.

3.3.1 Cluster summary

3.3.1.1 Strategy: whole-of-organisation view

This cluster speaks to **the importance of senior institutional leaders setting a strategic direction and signalling the organisation's commitment**. This can be achieved by integrating LA with long term planning and committing to direct investment. A number of statements within this cluster also spoke to the need to incorporate the full range of student data systems. Taken together, this overall strategic setting and the high level coordination of the IT systems cements the requisite conditions for an organisation-wide and resilient implementation. The function of this cluster can therefore be seen as a cultural and systems precursor: the organisation's leadership creates normative pressures and then facilitates capacity by aligning the IT infrastructure and its data products.

3.3.1.2 Compatibility with existing values/practices/systems

This cluster suggests that strategic direction is best achieved through an **engagement with a diversity of stakeholders and an understanding of how the organisation is currently aligned**. This speaks to the need for strategy to be sensitive to each institution's particular conditions, a bespoke rather than ready-made approach. As such, its function is to engage the culture, to reveal existing conditions, and adapt aspirations accordingly.

3.3.1.3 Data platform: standards and governance

This cluster revealed a bi-faceted approach to data stewardship. The panel's collective response indicates that the deployment of LA requires a platform where data can be easily shared within the institution. The development of conventions for the interpretation of data events and standards for identifying data instances are essential preconditions for the flow of data that is necessary for crucial comparisons (e.g. better/worse). But broad implementation and the concomitant **capacity to distribute data have implications for governance, chiefly the security of the data and the ethical protocols** that underpin its use. In that respect the capacity to share entails the necessity to secure data.

3.3.1.4 Data use: accessible, transparent, valid/reliable

While the previous cluster was concerned with the underlying principles of data description and protocols for exchange, this cluster refers to the conditions for data use. As such this is the first cluster to invoke a bottom-up, rather than a top-down, view. How accessible, manipulable, and confirmable is the data from the end users' point of view? The claim here is that it is better to see data as testable and the results or outputs (e.g. student risk) as conjectures, and the subsequent recommendations (e.g. for interventions) as hypotheses. This claim argues against a simple reliance on ready-made data outputs derived from opaque assumptions that do not allow end-user interrogation. These are the data requirements for **active, critical engagement with analytics representations, rather than passive consumption**. Essentially, the assumption is that the transparency of data and LA operations is critical to promote understanding and uptake.

3.3.1.5 Actionable tools with an evidential base

This cluster refers to the practical outcomes that must be demonstrated if LA is to have a long-term impact. The key question is whether LA contributes to the improvement of student learning and can be empirically demonstrated to do so. **Tools that are user-friendly and provide comprehensive and targeted feedback** are important elements of a pragmatic program for achieving this outcome. This cluster invokes the concept of a reflective learning system where tools improve with respect to their capacity to help educators and students achieve user-defined aims.

3.3.1.6 Conditions for educator adoption

The primary implementers are the educators. The designation 'educator' covers all those charged with the design and delivery of the 'products' of the system, chiefly courses/subjects, encompassing administrative, support and teaching roles. The elements put forward within this cluster are imperative for educator uptake. **These include co-designing with educators new analytics-enabled work practices that are sensitive to their environments, meeting and extending their pedagogical requirements, and ensuring flexibility and rewards.** 'Rewards' refers to the importance of both extrinsic and intrinsic (e.g. valuable formative feedback) motivators as a key driver for the diffusion and the integration of LA as standard practice

3.3.1.7 Supporting student empowerment

While the aforementioned cluster *Actionable tools with an evidential base* suggests the outcome of LA should be demonstrable improvements to student learning, this *student empowerment* cluster refers to the student experience (they should value the tools), the kinds of learners that we want to create (e.g. self-regulating and autonomous learners), and the specific processes through which this is achieved (e.g. by increasing their awareness of peer activity). **Learners here are conceived as having – or needing to develop – agency.** The role of LA in these statements is to empower students to take increasing responsibility for their own learning, rather than control student behaviour or mechanically direct students to resources.

3.3.2 Relative importance and feasibility

The expert panel also rated each statement on two scales, importance and feasibility. The average of these importance and feasibility ratings were then calculated for each cluster. Appendix R shows the pattern match at the cluster level for these scales.

Overall the panel found that what was important was also feasible, with no significant differences found between each clusters' perceived importance and its perceived feasibility. However, within the scales there were some notable differences. The cluster *Actionable tools with an evidential base* was considered significantly more important than a number of other clusters: *Data platform: standards and governance* ($t(18)= 3.15$ $p< 0.01$)*, Data use: accessible, transparent, valid/reliable* ($t(17)=3.03$ $p< 0.01$)*, Compatibility with existing* *values/practices/systems* ($t(16)=2.89$ $p< 0.02$), and *Strategy: whole-of-organisation view* ($t=2.22$ $p< 0.05$). There were no significant differences with the clusters *Conditions for educator adoption* and *Supporting student empowerment*. This indicates a demarcation in perceived importance between the three clusters that align with implementation practice (indicated by a blue square in Appendix R) and the four clusters that are concerned with strategy, policy and IT settings (indicated by the red square in Appendix R). This is an important insight as it reaffirms the dominant finding in the diffusion of innovation literature in general and the IT innovation deployment literature in particular: program failure is often due to implementation issues rather than strategic decisions, yet the former are often devalued [43, 44].

3.3.3 Summary

Taken as a whole, this analysis suggests that for LA to have a continued impact, the executive makes strategic decisions and coordinates the underlying infrastructure and systems. This is an exercise in organisational design and system calibration; resourcing and incentivising to foster an innovative evidence-based culture. This strategic backdrop supports flexible implementation practices and continual tool and data refinement that is responsive to the local needs of educators and students. This sensitivity to user aspirations in turn promotes an intrinsic motivation to learn and educator and student self-directedness. Implementation is conceived less a recipe-driven approach where LA is something "done to" educators and students, than as something done with them in partnership [45].

Chapter 4 - Discussion

4.1 Introduction

The findings from Study 1 and Study 2 provide rigorous insight into the current operationalisation of learning analytics (LA) implementations in the Australian context. The following discussion is framed in terms of the report's research aims, and its conceptual and empirical contributions to sector-level understanding of LA in higher education institutions. The report's overarching research aims were to:

1. determine the current state of LA in the Australian higher education context, including insight into institutional goals, plans, preparation and implementation activity;
2. determine relationships between institutional LA and retention activity; and
3. elicit insight into key affordances and constraints of sustainable and effective LA implementations in the higher education context.

4.2 Research Aim 1 – Current state of LA in the Australian high education context

Despite the burgeoning interest in LA and the potential that it affords institutions, LA implementations in the Australian higher education context are largely in the early phases of development. Approximately half of the institutions participating in this report had not implemented a LA program at the time of data collection (July 2014). The majority of programs that had been implemented were also limited in scope and relatively recent initiatives. These findings are consistent with early work undertaken by Bischel [46] and more recently Ferguson, et al [4] noting that despite significant investment, institutional adoption of LA remains relatively immature. In the present report, no university was able to point to a specific program that had been implemented at scale across their institution. Of course, a critical element shaping these findings may rest in the infancy of LA within the Australian higher education context. While, organisational and performativity data analyses have long been adopted in education, the application of data analytics for learning purposes is only recently receiving attention [47]. Hence, as a relatively new construct in the education landscape it is possible that institutions have not had sufficient time to effectively implement and evaluate LA programs. Regardless, clearly there are other elements at play confounding LA maturity of adoption.

The data solicited through interviews with senior leaders highlighted multiple issues and dimensions that appear to mediate LA implementations. These could be grouped into three dominant themes. First was the insight gleaned into LA's complexity and multidimensionality, second was the emergence of two trajectories of LA implementations across the Australian HE sector, and third was the identification of dimensions that appeared to play a critical role in the early development of LA implementations. These themes, and their implications vis-à-vis the current state of LA in the Australian HE context are discussed in turn.

4.2.1 LA as a complex phenomenon

The development and application of the multidimensional coding framework allowed LA implementations to be interrogated as complex phenomena, shaped by multiple, interrelated dimensions traversing conceptual, operational and temporal domains. Further, the cluster analysis revealed the relative salience (operationalised as statistical significance) of the different dimensions, and inter-relationships between them. LA implementation emerged as a non-linear, recursive, and dynamic process, with LA implementation outcomes mediating, but also mediated by, antecedent concept and readiness dimensions in an iterative loop. While the conceptual literature highlights the multidimensional and complex nature of LA implementations, limited empirical literature has accommodated its complexity, thereby denying insight into how LA actually 'works' and 'looks' across a wide range of variables. The studies in this report provide insight into how such research could be operationalised in future.

The practical significance of the complexity of LA lies in the associated implications for institutional leaders responsible for LA implementations. The emergent, non-linear and cyclical presentation of LA unearthed in this report challenges many of the traditional conceptual models and depictions of LA, particularly those seeking to represent linear and step-wise process. Enacting on these findings will necessarily challenge many of the traditional organisational, management and curriculum structures that exist within an institution. This is in part reflective of the origin of LA in bringing together both technology and learning (traditionally separate organisational units in university structures), as well as its rapidly changing, dynamic and iterative nature. As such, any long term and large scale implementation process will require management and leadership structures to be equally responsive and accommodating. This leads to questions as to what structures are fundamentally aligned with the processes for LA implementations. Here, we suggest that the mature foundations for LA implementations were identified in institutions that adopted a rapid innovation cycle whereby small scale projects are initiated and outcomes quickly assessed within short time frames. The successful projects in this cycle are then further promoted for scalability and mainstream adoption. In the context of LA, this small-scale seeded approach appeared more effective in terms of organisational acceptance and adoption than a whole of institution model attempting to roll out a single encompassing program. As such, these findings suggest that that the sector can further grow its LA capacity by encouraging institutions to engage in similarly diffuse, small-scale projects with effective evaluation that quickly identifies sites of success and potential impact. In essence, while LA provides a strong research layer to higher education, its successful adoption is dependent on an institution's ability to rapidly recognise and respond to organisational culture and the concerns of all stakeholders.

4.2.2 LA as two distinct trajectories

The finding of two distinct trajectories of LA implementation highlighted the contextual, situated nature of LA, and revealed insight into how and in what ways institutions were diverging in their approaches to LA implementations. In the first trajectory, LA was primarily focused on supporting retention activity. By contrast the second trajectory was characterised by emerging focus on LA for pedagogy, curriculum, and learning. The data suggested that institutions not only differed in terms of how LA was operationalised and looked within their institution, but importantly found that these differences were owing to diverging conceptualisations and understandings of LA. Commonly the LA literature will attribute variance in LA outcomes to temporal dimensions. An implicit assumption guiding LA literature has been that, over time, institutions will ultimately converge in their LA aspirations and implementations. However, the findings in this report suggest the converse: that over time, institutions may continue to diverge in their LA operationalisations. Indeed, how an institution conceptualises the drivers and purpose of LA appears to mediate how LA is operationalised not just in the present, but also its trajectory in the future.

A particularly pressing manifestation of the two clusters for practitioners lies in their foci. While all institutions identified retention as a priority activity for LA, Cluster 1 institutions primarily utilised LA to support targeted retention activities. By contrast, Cluster 2 institutions were supplementing their retention activity with the development of structures and resources (Readiness Variables) that would support LA initiatives designed to enhance teaching and learning experiences more broadly. Taken at face value, this would suggest that the next phase of LA maturity for institutions in Cluster 1 relates to strategically focusing on readiness variables to ensure that they can accommodate and support LA activity that is embedded in, and informs, teaching and learning activity. However, this report's finding of strong relationships between Concept, Readiness and Context Variables highlighted the need to consider LA implementation as involving more than tangible, overt structures, and reinforced the critical role of underlying epistemological, ontological and contextual elements in mediating outcomes. These themes are explored in the following section.

4.2.3 LA is multidimensional

Across all institutions, 6 mediating dimensions of LA activity emerged as particularly salient. These were the role of institutional conceptualisations of LA on actual implementations; the need for highly-focused and influential leadership; an appropriate and sustaining structure supported by articulated vision and strategy; technological competence; and context. These dimensions are discussed in turn.

4.2.3.1 Conceptualisations of LA

On initial review, the finding of a relationship between how a leader conceptualises LA, and how it is ultimately operationalised within their institution, appears logical, and in many respects supports the conceptual and empirical claims attesting to the importance of a clearly-communicated and understood vision for successful LA implementation. However, the findings of this report have far deeper implications. The results indicate that while strategic vision is important, underlying epistemological and ontological values also shape the practical pathway for achieving the vision. That is, establishing a vision and identifying how to 'solve' the problem that LA was intended to address was not nearly as critical as how the 'problem' was initially framed, nor the assumptions that underpinned such framing.

The salience, and statistical significance observed for the potential of conceptual dimensions to mediate LA implementations was not expected. Indeed there appears to be a paucity of literature that specifically explores relationships between meaning making of LA and actual operationalisations. By contrast the current research highlighted how senior managers of institutions and even units across institutions diverged in their understandings of LA, and found evidence of (non-causal and possibly recursive) relationships between these conceptualisations and actual LA outcomes. It is therefore possible that, in some instances, leaders' constructions may inadvertently be constraining the potential of LA within their institution.

4.2.3.2 Leadership

Leadership's emergence as a critical dimension in LA implementations lends further weight to the extensive conceptual and empirical studies claiming its importance. A significant, element was the insight afforded into leadership as a multidimensional practice. Leadership appeared to mediate implementation outcomes through both structure and style. Interestingly, leadership structure (distributed or centralised) did not have a significant effect in the cluster analysis. Leadership structures were evenly distributed across the sample, with 18/32 institutions adopting a distributed leadership model. Distributed leadership models are based on shared, empowered and distributed systems of ownership and leadership, and advocated strongly in the emerging leadership literature as ideal for organisational contexts that are complex, emergent and dynamic [48, 49]. However, distributed leadership models also pose challenges to the traditional university organisational and leadership structures. Related, the operationalisation of "leadership scope of influence" to incorporate multiple elements (including an ability to secure organisational mandate, and evidence of knowledge of the field of LA), appeared to highlight the importance of leadership that is both informed and grounded in knowledge of the field [50]. However, it is difficult to determine whether the knowledge was itself an affordance and precursor to, or a product of, effective LA leadership. The report's findings suggest that leadership should be afforded a more discriminating and nuanced scrutiny in future research to better understand how different leadership processes, structures and styles mediate LA implementation outcomes.

4.2.3.3 Strategy

The mediating potential of strategy was also confirmed, and further validates the conceptual and empirical literature suggesting its importance. Operationalised as the development of a strategy, it was found that an institution's stage of strategy development typically correlated with the strength and scope of leadership exhibited within it, and ultimately the institution's level of readiness for, and conceptualisation of, LA. There is logic to this finding. The generation of strategy within higher education institutions is an activity that typically assumes time, and effective communication with a range of stakeholders. In the case of LA, it involves the bringing together of traditionally disparate organisational units within an institution in a project context that is fluid, rapidly changing, and relatively unchartered: there is very little precedent to guide universities on how LA can or could look as embedded in standard teaching and learning functions. It is perhaps owing to LA's unorthodox and emergent nature that leadership and strategy assume heightened salience in the early stages of LA implementations.

It is worth noting that the strategic positioning of LA (operationalised as where and how LA was situated and structured within an organisation) varied across institutions. Some institutions embedded LA in existing functions, others created independent LA units. Further, some split LA across multiple organisational units. Underpinning these decisions was broad recognition of LA's multidisciplinary nature, encompassing IT, pedagogical, data, and student support domains. While this report did not find a significant relationship between strategic positioning and LA outcomes, it is possible that this may be owing to the relatively nascent stage of LA within institutions. As LA grows in profile and scope within institutions, it is possible that decisions vis-à-vis how LA should be positioned and structured may take on further significance.

4.2.3.4 Stakeholders

The findings from this report noted that people form a critical ingredient in the early stages of LA implementations. In essence, stakeholder feedback and capacity building emerged as significant dimensions. In light of the findings associated with leadership and strategy, the significance of stakeholder consultation is not surprising. Institutions appeared to engage in one of two levels of consultation: either primarily focused on senior management, or involved a broader institutional profile (such as academics, students and professional staff). Stakeholder engagement that was limited to senior management was typically associated with more traditional levels of management and a less developed strategy. By contrast, institutions engaging in comprehensive stakeholder engagement typically reported a high level of leadership commitment and input and demonstrated more mature and comprehensive strategies. Perhaps the very process of broad stakeholder engagement, not only solicited the diversity of needs and goals, but also functioned as a vehicle to communicate the strategic vision, directions and priorities, thereby reinforcing many of the benefits associated with strategy development.

The findings also affirmed the mediating potential of organisational (stakeholder) capacity. The analysis did not scrutinise types of organisational capacity issues. Rather, the focus was simply on whether or not institutions were actively addressing capacity through the development and implementation of targeted programs and initiatives. Most instances of targeted, capacity building programs were found in Cluster 2 institutions. By contrast, capacity programs were undeveloped and had not been implemented in Cluster 1 organisations. Institutions that incorporated such programs also typically adopted more complex and less instrumental conceptualisations and operationalisations of LA.

4.2.3.5 Technology

As a pillar of LA, it is not surprising that technology was revealed to be a significant mediator of LA implementation outcomes. Critical to the success of any LA implementation is the establishment of sound technical infrastructure. Most commonly, the establishment of an Enterprise Data Warehouse (EDW) provides ease of access to data and therefore can facilitate wide access to data analyses and reports. Of the ten institutions that had not implemented an EDW, eight reported no LA program: its absence appears to constrain the establishment or at least the commencement of institutional LA projects. The data capacity of the EDW's diverged across the population sample. While some institutions had linked their data warehouse to dynamic, LMS data, and other forms of student experience across the campus (such as library usage), in other institutions the EDW was only host to student demographic and progress data. Further, there appeared a relationship between the types of data accommodated in EDWs and broader conceptualisations and operationalisations of LA. Cluster 2 institutions contained EDWs with more comprehensive data sources.

When compared to other 'readiness' dimensions of organisational capacity and organisational culture, technology readiness was more developed. These findings suggest that technology readiness takes precedence over organisational culture and capacity in the early stages of LA implementations. Interestingly technology enhancements included products developed in house and also external to the organisation, with the majority of initiatives incorporating elements of both. However, the data suggests that the adoption of vendor products in Cluster 2 was accompanied by a more critical, circumspect awareness of their capacities and limitations.

4.2.3.6 Context

While the context dimensions operationalised in this report did not emerge as statistically significant, the findings did highlight LA's situated and contextualised nature. LA implementations appeared to be shaped by an institution's conceptualisations, understandings, and drivers of LA, these in turn are mediated and informed by broader institutional goals and factors. For instance, institutions with low retention and success rates appeared more likely to directly focus on retention-related interventions than a broader view of how LA can shape institutional learnings. By contrast, institutions with higher retention and student success outcomes were more likely to demonstrate apply a wider view of LA with an emerging learning focus. It is suggested that future research into LA implementations further scrutinise how, and in what ways, context mediates the conceptualisation of LA. The lack of statistical significance found in this research may also be owing to the narrow operationalisation of context adopted within it, and it is argued that future research could incorporate a broader conceptualisation of context to embrace the "external constraints bearing on interactions and representations" [51], such as social and institutional structures.

4.2.4 Conclusion (and a model of Strategic Capability)

Collectively, the above themes present a possible model of strategic capability that captures enabling qualities of LA implementations. These are captured in the Model of Strategic Capability presented in Figure 5. In this model, the 6 enablers of Conceptualisation, Leadership, Strategy, Stakeholders, Technology and Context are represented in a dynamic, systems model. Relationships within the model are recursive, with LA implementation a fluid and dynamic response to these inter-relationships. A possible outcome of this conceptualisation is that the experience gained from developing and implementing initiatives may modify the enablers and their interconnected relationships, perhaps facilitating iteration and transformation. The model therefore draws attention to the temporal dimension of LA and its influence on the development, maturity and evolution of individual and collective components. In addition to pushing strategic capability forward, the temporal dimension also exerts direction of motion and has a rotational effect, which shifts enablers into, and out of, focus. This is evidenced by the variance observed in readiness variables across universities, and their likely influence on LA implementation.

This model does not, however, capture fully the relationships between LA implementations and broader retention agenda. The second part of this discussion will explore this relationship. The third and final part of this discussion highlights the conceptual linkages between the two studies.

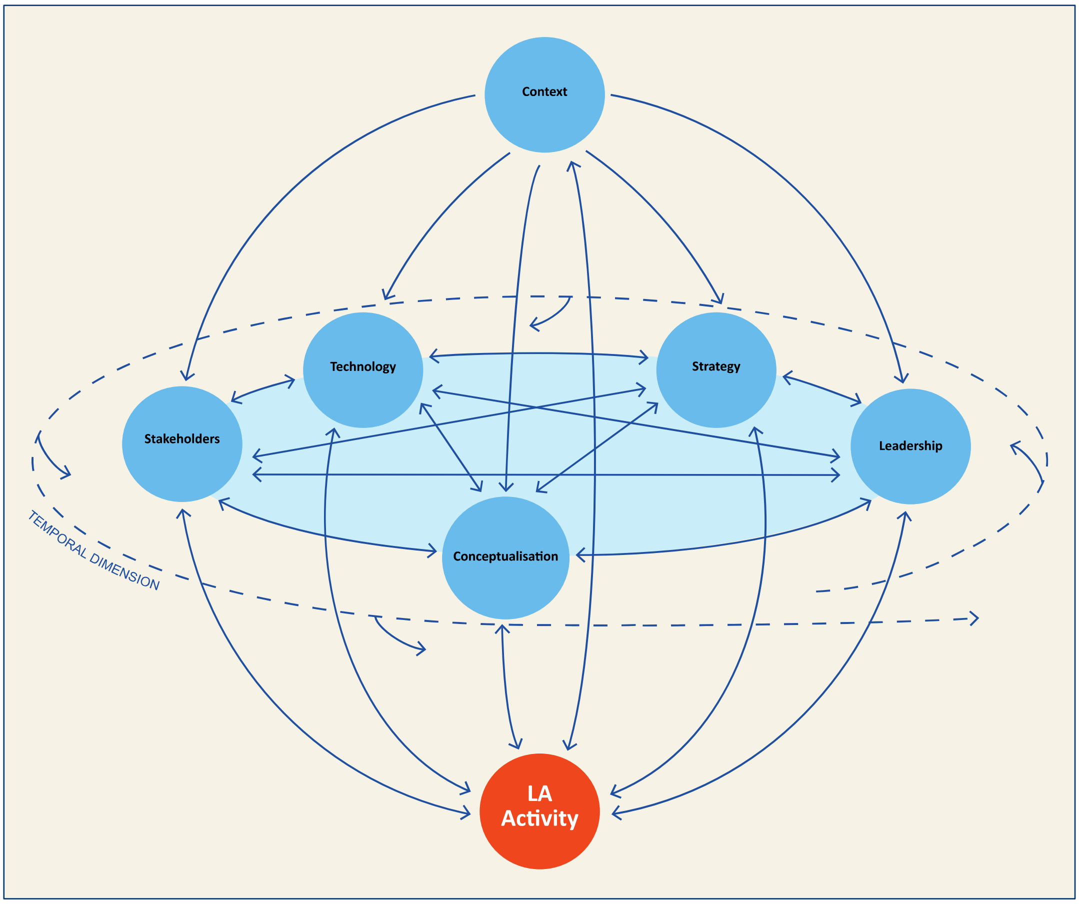

Figure 5. Model of Strategic Capability

4.3 Research Aim 2

4.3.1 Relationships between institutional LA and retention activity

The conceptualisation and operationalisation of retention emerged as intrinsic to, and embedded within, institutions' broad LA aspirations. All institutions identified retention as a key driver for LA activity. However, within this overarching paradigm of a LA-retention nexus, there emerged significant qualitative differences across institutions vis-à-vis how retention was 'constructed' and ultimately addressed through LA. Two clear trajectories of LA-related retention activity were identified, with these trajectories distinguished, and defined by, underlying ontological and epistemological understandings and objectives (Concept variables), as much as by stages of readiness and actual implementation patterns. Curiously there emerged a relationship across institutions between their conceptualisations and understandings of LA (to measure or understand), their identified drivers for LA (learning-retention only, or learning-retention and efficiency) and their notions of retention (as a reified phenomenon removed from antecedent, or a phenomenon distally connected to university-related antecedent factors). These appeared to mediate actual LA implementations.

Interpreted through the Model of Strategic Capability (refer to Figure 5), institutions identifying measurement and retention as their ultimate motivation demonstrated an ability to move effectively and efficiently through planning to the implementation of retention-related LA outcomes. For the majority of these institutions, retention was conceptualised as an independent, reified and proximal phenomenon, and LA-interventions appeared to be predicated on this premise. Common were programs that identified and contacted students at-risk through primarily distal, demographic data. Within this Cluster there was very limited or no evidence that institutions were preparing to extend their LA activity to teaching and learning domains. In contrast, institutions who conceptualised retention as embedded and interdependent demonstrated evidence of movement of LA initiatives beyond a retention focus and toward using LA as an enabler for broader, more holistic retention and student success strategies.

The model also highlights the influence of context. This may further explain the observed divergence in the conceptualisation of retention between universities, and subsequent implementation of LA activity. For institutions with immediate concerns regarding retention it is understandable that LA activity is powered by notions of instrumentality. Thus, a requirement to demonstrate return on investment over a short period of time narrows the framing of retention, and the subsequent focus of LA. Simply put, the core driver for LA implementation is to facilitate resolution of a particular issue. As such, there is limited consideration as to how LA may also contribute to other teaching and learning domains until the most pressing concern has been addressed. It is possible that the emphasis of the early analytics literature on predictive modelling and retention has also inadvertently constrained institutional understanding of the broader applications of LA to improve learning and teaching practice [52]. In this context, the availability of commercial products designed to identify at-risk students neatly fits the perceived need, appears to offer an institution-wide solution, and does not necessitate (hard or impossible to find) investment in internal research and development efforts.

Conceivably, we may contrast these as follows with the larger and more technologically advanced institutions in the other cluster. These universities demonstrate greater in-house capability in the learning and data sciences, lending itself to a more critical perspective. Many of universities in cluster 2 were seemingly under less pressure to combat attrition and demonstrate immediate gains from expenditure, they are comparatively afforded a greater amount of time and opportunity to broaden their conception of what LA may offer, and hence extend the application of their LA programs beyond a pre-defined vendor solution to “the retention problem”.

4.4 Research Aim 3

4.4.1 Affordances and constraints of LA implementations.

Cluster 1 and Cluster 2 represent strategic choices, even if inadvertent ones. It is instructive to contrast these two empirically uncovered clusters with the findings of the concept mapping exercise. Of the two clusters, Cluster 2 suggested a broader view of LA that is much closer to the conditions for sustainable uptake of LA indicated in our concept mapping investigation (Study 2). The conceptualisation of LA emerging from the concept mapping exercise suggests learning and capacity building, rather than immediate instrumental gains in retention, are central to planning for effective long-term adoption. It also acknowledges the difficulty of the cross-silo, horizontal nature of LA implementation. Within this conceptualisation, leadership is local and distributed, where it can be responsive to salient changes in the environment. Yet it is recommended that this immediacy in LA leadership and implementation be coordinated if it is to serve an institutional purpose and not fragment the learning opportunities and efficiency dividends that it could afford. There would be, for example, little sense in creating multiple and competing risk metrics and dashboards for students and teachers. Coordination implies the existence of a strategic direction, stakeholder consultation and buy-in, and the development of institution-wide technology and data that can underpin local level LA initiatives.

The combined findings from the two studies suggest sustainable learning analytics adoption consists of a number of mutually influencing resources and assets located in a complex system. To represent this we draw on the field of system dynamics [71] to illustrate the way resources 'flow' from one accumulated state, or 'stock' to another, how stocks influence the flow rates of other stocks, and how feedback effects link them. Many of the variables that support learning analytics adoption identified in this investigation constitute stocks of capabilities in the technical sense of "activities groups are good at doing that can be and often are deliberately identified and developed" [70]. Two key capabilities were identified, a strategic capability that orchestrates the setting for learning analytics, and an implementation capability that integrates actionable data and tools with educator practices. These capabilities are the essential drivers of the flow rate that pushes/pulls educators along the educator uptake pipeline from 'interested' to 'implementing'. The report findings imply two additional drivers. First, implementers require an analytic tool or combination of tools that manage data inputs and generate outputs in the form of actionable feedback. The capacity to implement is crucially linked to the quality of these tools and the data they rely on and generate. Second, this in turn requires an organisational learning capacity to monitor implementations and improve the quality of the tools, the identification and extraction of the underlying data, and the ease and useability of the feedback interface. As these increasingly meet the real needs of learners and educators the organisational uptake is accelerated. Thus, the elements identified have the potential to act in concert forming a reinforcing feedback loop. The strategic capability can also directly affect the flow rates into the implementation capability (for example by funding the recruitment of specialists) and facilitate the flow to implementing (for example through organizational rewards). Figure 6 shows the key stocks and flows in this system, their influence on each other, and the major reinforcing feedback effect.

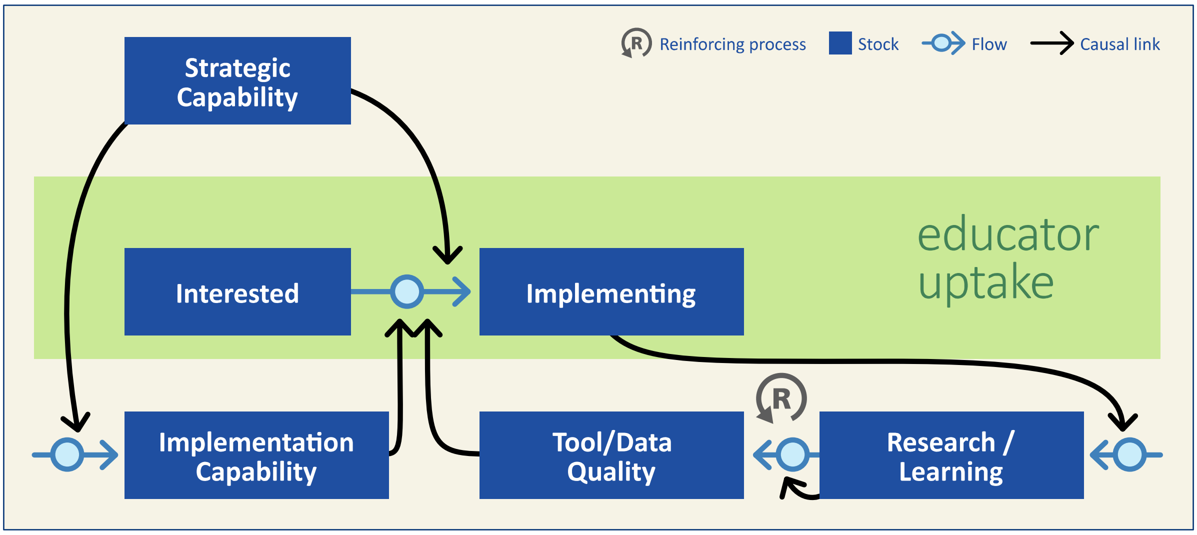

Figure 6. Model of system conditions for sustainable uptake of LA

Cluster 2 institutions appear to have adopted an embryonic version of this model. Their strategic capability is designed to foster a systemic resilience that is responsive to future, unknown diversity – in the kind of student, the pathways those students will adopt through their learning, the models of teaching that will be most effective, and the means of delivery utilised. In this model LA fosters a long-term organisational learning capacity.

By contrast, implementations in Cluster 1 appear to be designed to address an immediate need. In this instance, LA is largely focussed on the discovery of students at risk. This may be drawn from predictive models that are then coupled with an institutional communication response, usually by a dashboard or direct contact, designed to re-engage students with their studies. This process runs the risk of limiting the potential of LA for the correction or enhancement of learning design, course delivery, and curriculum structure. While the adopted approach may aid retention through (commonly outsourced) interventions, it has limited scope for organisational learning.

We acknowledge these characterisations, although empirically justified and important, are artificially binary. These represent continuums of general patterns at a distinct point in time. There are certainly some institutions combining both approaches. There is also the issue of priority. For some universities stemming a chronic retention or academic performance issue understandably trumps other considerations in LA implementation in the short to medium term. The inclusion of 'context' as a mediating variable in our Strategic Capability Model (Figure 5) is designed to accommodate these possibilities.

In our introduction we flagged the problem of the slow uptake of LA despite its well-acknowledged promise to help universities address their contemporary, and potentially conflicting, demands to improve quality, widen student intake, and demonstrate improved efficiencies. Our investigation suggests two related factors are involved, complexity and feedback. To implement LA is, as we have emphasised, complex. There are many moving parts and coordination among them is important. The whole-of-institution LA capability envisaged in our concept mapping process relies on cross-institutional communication of the highest order, and a jointly held commitment to an evidence based culture.

4.5 Recommendations

This report has provided insight into the current state of LA implementations in the Australian context and the array of mediating conceptual and structural factors that are shaping how LA is being utilised. Overall there is positive interest in LA and its potential. However, implementations are at early, nascent stages.

The report has highlighted key areas that require strong consideration if LA is to provide long term and meaningful impact for higher education institutions. These include:

4.5.1 Conceptualisation

Capabilities are required at both the strategic level and the implementation level. How you frame the problem defines your notion of a solution. The relationship between conceptualisation and visions of LA and the nature of LA outcomes (particularly retention-driven LA) highlights the need for continued discussion among senior leaders as to the purposes, goals and underlying ontological positioning underpinning LA in higher education. International peak bodies such as SoLAR could take a key role in leading this agenda.

4.5.2 Capacity and Culture

The low salience afforded to these two dimensions in the implementation agenda was surprising, but may in part be owing to the infancy of LA implementations in general, rather than a reflection of their importance. It is probable that these dimensions will assume greater salience as LA agenda become more mature. In light of this, the sector would benefit from the identification or development of resources and programs aimed at assisting institutions in assessing their readiness in these two key areas.

4.5.3 Leadership

Not only was leadership revealed as a critical dimension in shaping LA outcomes, it was also revealed as a multidimensional construct encompassing influence, knowledge, commitment, and structure. A more nuanced conceptualisation of LA leadership is required both operationally and in the literature. Over time, it is hoped that leadership models can be empirically tested against actual LA outcomes.

4.5.4 Rapid Innovation Cycle

The findings highlighted the benefit that can be gleaned from implementing small-scale LA initiatives, and growing the scope and scale of these programs, rather than aspiring to the generation and development of an 'at-scale' initiative in the first instance (an objective that is often encouraged in the conceptual literature [50]). The findings in this report suggest that implementing early and to small scale, even if inadequately, will build capacity.

4.5.5 Ethics

The relative silence afforded to ethics across both of the studies is highly significant, and does not reflect the seriousness with which the sector should consider these issues. In North America, UK, South Africa and Europe significant resources have been devoted to the development of tools and resources to guide institutions through the many ethical implications and challenges that LA presents. It is likely that the higher education sector has not been ready for such a conversation previously, although it is argued that as institutions are maturing, ethical considerations take on a heightened salience. It is recommended that a national conversation be initiated in which ethical considerations will be identified, framed and possible actions identified.

Appendices

Appendix A: Certification by Deputy Vice Chancellor

Certification by Deputy Vice-Chancellor (or equivalent)

I certify that all parts of the final report for this OLT grant/fellowship (remove as appropriate) provide an accurate representation of the implementation, impact and findings of the project, and that the report is of publishable quality.

Name: Allan Evans Date: 15 June 2015

Appendix B: Study 1 Interview Protocol

Introduction

Short explanation of the purpose of the study: to better understand the policy and strategic issues surrounding implementation of LA at their institution. The timeline under consideration is 0-5 years. Particularly for senior managers the emphasis is on 'how your *role* perceives the following…'. For each set of questions a follow-up with What, if any, are the successes, gaps or lessons learned you've found with this approach?

A. Overview

1. What is your current thinking about Learning Analytics? (extrapolate what DVC sees/understands as LA)
2. What benefits do you think Learning Analytics might provide for your institution?
3. Is your institution currently implementing a Learning Analytics project/initiative, or do you plan to within the next 5 years?

B. If current implementation, please describe your project to me.

4. What is the primary purpose(s) for implementing LA at your institution?
   a. related to improved teaching quality,
   b. reduced costs,
   c. quality assurance,
   d. pastoral care,
   e. student retention
5. When did your institution become interested in Learning Analytics?
6. Who or what is driving/promoting the LA initiative on campus? (Research, L&T/support, IT, Admin, Schools, other?) Probe - have different areas 'taken on' the LA agenda at different times?
7. Can you describe the LA model(s) that you are using?
   a. Is the development largely in-house, outsourced, or a mixture?
   b. What are the circumstances or the reasoning behind these choices?
   c. Are there leaders in the field, strategies or examples informing your choice of LA model [what makes those models appealing?]
8. Is it a one-off or part of a series of initiatives?
9. Will the data generated by LA be used internally for research and innovation?
10. What is your perception of your organisation's current preparedness to implement the initiative(s) and follow-up on the data that is generated?
    a. (do you have any gaps or capacity building to ensure your strategy will be successful - if so where are these gaps and do you have any thoughts on how to overcome them?)
11. What barriers or challenges have you faced in rolling out your LA strategy?
12. How are you evaluating these initiatives or what will success look like?

C. Strategy and Policy

13. Do you have an explicit strategy for LA or the use of data informed approaches? [How does it align with key visions, organisational objectives, and KPIs?]
14. Does your institution have explicit written policies or procedures surrounding LA? If so, would you be willing to share them with me? If not, do you expect to develop these and do you have a timeline for doing so?
15. Is there a governance structure and/or committees that oversee LA work? Please describe it to me?
16. Do you offer any incentives to faculty/department to implement LA practices, or other approaches for getting buy-in?
17. Have you reviewed existing university policies regarding matters such as student assessment, privacy, ethics, and feedback, in light of LA initiatives at your institution? If so, which ones? (prompt for those that address assessment, student feedback and grade reviews)
18. Do you have a process or procedure for regular review of LA activity at your institution? Could you describe this to me? (probe, is it embedded in a framework of continuous improvement)

D. Resources and Timeline

19. How did your institution determine the resource needs for LA?
20. What technical and/or human resources were required?
21. Does your plan involve stages of deployment? If so, what are the stages? And is there a timeframe governing each stage?
22. With regard to human resources, what is the makeup of the main team driving LA at your institution (eg IT specialists? Faculty? Senior management?). Probe the reasons why different areas represented in the teams
23. Has the make-up of team(s) changed or stayed the same though the life of LA, or is it fluid/dynamic. Probe - examples/why changes/why not changes
24. What is the amount likely to be invested, both in terms of initial investment and recurrent expenditure? Is there a timeline attached to any funding (e.g. stages of development)?
25. Are there any key points we did not cover adequately with these questions? What kind of information from this research would be of benefit to you? (Added after first four interviews)

E. If planning an implementation, please describe your plans to me.

(NEED TO ADD SOME PROMPTS ALONG THE THEMES ABOVE TO HELP THEM DESCRIBE IN MORE DETAIL).

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Appendix C: Study 1 Preliminary Analysis

A preliminary analysis of interview data was performed according to the following steps:

Step 1

Interviews were transcribed and a preliminary, inductive, exploratory analysis was performed to identify and extract potential ideas and meaningful information. A process of coding was conducted, where text relevant to the research aim of exploring learning analytics antecedents, processes and implementations was highlighted and assigned to a label to capture its meaning. Text with similar meaning was therefore coded and subsequently grouped together. This process generated more than 120 coding tags, which were then loosely grouped into 36 categories, and effectively gleaned insight into the saliency and frequency of ideas emerging across the data. Categories that emerged as most salient included retention, strategy, vendors, challenges, types of analytics, ontology, learning and technology.

Examples of the groupings of tagged ideas into categories is shown in Table 1.

Table 1

Examples of preliminary tags grouped into categories

Preliminary Tags	Category
Centralised; Governance; Institutional Uptake; Planning; Policy; Project Management; Strategic Framework; Structure	Strategy
Barriers; Resistance; Finances; Staffing Issues; Structure	Challenges
Academic Analytics; Assessment; Dashboard; Demographic Analytics; Predictive Analytics; Social Networking Analysis	Type of Analytics
Big Data; Domains; LA for Retention; LA for Teaching and Learning; Measurement; Techniques	Ontology
Blended Learning; Collaborative Learning; Game Learning; Learning Models; Learning Strategies; Personalised Learning; Student Learning; Teaching Benefit; Understanding Learning	Learning
Infrastructure; Investment; Learning Management System; Open-Source; System Design; Systems and Platforms	Technology

Step 2

The current learning analytics literature was reviewed and conceptual lenses, frameworks and maturity models of learning analytics implementations, through which the data could be analysed and compared, were identified [for example 34, 48, 53].

Step 3

Ideas and categories obtained from coding in Step 1 were scrutinised and compared to extant conceptual learning analytics models from Step 2. This process revealed that, although interview data corresponded to, and reaffirmed components of theoretical frameworks within the literature, existing protocols did not adequately capture the complete range of themes emerging from the data, nor expose their multidimensionality both in complexity of content and depth of experiences. Notably, extant conceptual models typically operationalise key constructs within LA through a uni- or limited-dimensionality lens, whereas the data from interviews revealed greater complexity in how concepts were actually being conceptualised and operationalised.

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Appendix D: Study 1 Development of Coding Protocol

The new coding protocol developed gradually and rigorously by undertaking the following steps:

Step 1: Coding

A second thorough, inductive analysis of interview transcripts was performed by two researchers independently. This process was distinct from that in the preliminary analysis. Meaningful interview data and ideas were again coded and grouped. Examples of preliminary coding tags at this stage included 'Strategy-led', 'Policy', 'Technology Constraints', 'Stage', 'Goals', 'Devolved Leadership', and 'Committee'.

Step 2: Development of Themes

Themes were formed both deductively and inductively according to Braun and Clarke's [54] method of thematic analysis. Themes refer to predominant patterns of meaning within the data. Decisions around groupings of themes were further informed by Patton's [55] criteria, which states that themes must exhibit internal homogeneity (consistency), and external heterogeneity, in that they are distinct from one another.

It was the intent of the research to map the interview data against conceptually informed, pre-identified themes, including leadership, strategy, technological readiness, capacity, organisational culture, data and ethics. In the first instance, this involved scrutinising the inductively coded text to determine whether conceptual themes were present. The coded tags were then deconstructed, grouped and reorganised into themes.

Recurring ideas that emerged across the data but did not fit pre-determined concepts, such as the conceptualisation of learning and retention, informed new, inductively generated themes.

This process generated a total of 11 inductively and deductively informed themes: 1) Learning Analytics; 2) Retention; 3) Learning; 4) Data; 5) Analytics; 6) Leadership; 7) Vendor; 8) Strategy; 9) Stakeholders; 10) Mediators; 11) Implementation.

Step 3: Dimensions, Levels and Operationalisation

Through the preliminary analysis it was determined that the themes emerging from these data were multidimensional, with varied levels of complexity and depth with regard to conceptualisations and experiences. Themes were therefore partitioned into dimensions where appropriate. For example: the theme 'Learning Analytics' contained data concerning institutional conceptualisations of learning analytics *purpose* and *drivers*. Data for this theme was thus divided into the dimensions 'Purpose', 'Driver Quantity' and 'Driver Type'. This process was again informed both deductively and inductively, and lead to a total of 27 dimensions, detailed in Table 2.

Table 2
Final Themes and Dimensions

Theme	Dimensions	Weighting & Rationale
Learning analytics	Purpose	0 — 1
	Driver Quantity	0 — 1 — 2
	Driver Type	0 — 1 — 2
Retention	Conceptualisation	0 — 1 — 2
Learning	Conceptualisation	0 — 1 — 2
	Dimensionality	0 — 1 — 2
Data	Ontology	0 — 1 — 2
	Process	
Analytics	Focus	0 — 1 — 2
Leadership	Structure	0 — 1 — 2
	Scope of influence	0 — 1 — 2
	Sponsorship	0 — 1 — 2
Vendor	Vendor awareness	0 — 1 — 2
Strategy	Development	0 — 1 — 2
	Strategic position	0 — 1 — 2
Stakeholders	Consultation	0 — 1 — 2
Mediators	Culture	0 — 1 — 2
	Building capacity	0 — 1 — 2
	Technology	0 — 1 — 2
	Funding	0 — 1 — 2
Implementation	Ethics	0 — 1 — 2
	Stage	0 — 1 — 2
	Education Data Warehouse	0 — 1 — 2
	Scope	0 — 1 — 2
	Learning impact	0 — 1 — 2
	Vendor products	0 — 1 — 2
	Evaluation process	0 — 1 — 2

To reveal gradations of complexity across institutions, dimensions were further divided into discrete levels representing differences in experience and conceptualisation. All dimensions were operationalised into three levels. For example, data assigned to the dimension 'Building Capacity' was categorised into the levels 'Limited Awareness', 'Recognition' and 'Strategic Approach', with the Rationale for the criteria grounded in the literature as far as possible. The only exception was the dimension 'Learning Analytics Purpose', which was operationalised into two levels, 'Measure' and 'Understand'.

Operationalisation and formal descriptions of dimension levels were generated with reference to concepts and theories from learning analytics literature where appropriate. For instance, the theme of 'Leadership' emerged inductively from the data, but was interpreted and operationalised in reference to Complexity Leadership Theory [49]. For coded text that did not fit pre-determined concepts from the literature, such as conceptualisations of the purpose of learning analytics, operationalisations were constructed from the data.

Step 4: Quantizing

To facilitate further analysis and the recognition of patterns across the qualitative data, a method of quantizing was then applied. This involved the assignment of numeric values (0, 1, 2) to each of the three levels in order to capture the difference between experiences [56]. Whilst the majority of values reflected ordinal differences between gradations of themes, this was not true for all dimensions, such as where values merely represented a difference in conceptualisation or approach, as in 'Learning Analytics Purpose" and "Data Process".

For a final copy of the coding protocol see Appendix S.

Step 5: Coding procedure

Two researchers coded the data independently according to the protocol. After an initial pilot and comparison of coding for four participants an inter-rater agreement rate of 64.38% was achieved, with inconsistencies and an uneven distribution of discrepancies across dimensions. To improve clarity and strengthen homogeneity and heterogeneity within and between dimensions, the protocol was revisited and revised iteratively. Transcripts were recoded according to revisions, and cross coding of 16 transcripts was performed. This achieved a strong inter-rater agreement of 90.77%. It is noted that, in this second cross-coding, the researchers were unable to meet a satisfactory agreement rate for three dimensions which were therefore omitted from the final protocol and analysis.

The coding framework was then applied to all interview transcripts and a matrix was developed, where numerical values were assigned to every participant for each of the 27 dimensions.

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Appendix E: Study 1 Cluster Analysis Methodology

An exploratory cluster analysis was performed to identify similarities, differences and patterns of experience across universities. Due to the categorical nature of the data set, Partitioning Around Medoids (PAM) clustering, a k-medoids algorithm, was employed.

Dimensions were translated into variables, and results from the coding of dimensions, were organised into four variable categories: Concept, Readiness, Implementation and Context (See Appendix F & G). Universities were clustered on the basis of Concept and Readiness Variables, and compared on the basis of Implementation and Context using Chi-square and ANOVA tests.

The silhouette method of cluster validation determined that a two cluster solution was optimal for the current data set. This was achieved by identifying two medoids, that is, "exemplar" data points, or representative universities. Clusters were then formed around the medoids as a centre, on the basis of maximising within group similarity and minimising between group similarities. Gower's similarity index determined similarity between the medoids. This involved the calculation of a number between 0 and 1 to indicate the percentage of variables for which two universities have the same value. The medoids selected were University ID 7 (Cluster 1), and University ID 26 (Cluster 2). Gower's index determined similarity between the medoids, indicating the percentage of variables for which two universities converge to be 0.55, as the institutions agreed in 11 out of the 20 total variables. PAM was then performed to allocate the remaining universities to the clusters so that university dissimilarity to the medoid was minimised within groups.

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Appendix F: Study 1 Cluster Analysis Categories and Variables

Table 3:

Grouping of cluster analysis variables into categories

Concept Variables	Readiness Variables	Implementation Variables	Context Variables
LA Purpose	Leadership Structure	Ethics	University Group
LA Driver Quantity	Leadership Influence Scope	Stage	State
LA Driver Type	Leadership Sponsorship	EDW	City
Retention Conceptualisation	Strategy Development	Scope	City/Regional
Learning Conceptualisation	Strategy Strategic Position	Learning Impact	Enrolment
Learning Dimensionality	Stakeholders Consultation	Vendor Products	Retention Rate 2012
Data Ontology	Mediators Culture	Evaluation Process	Success Rate 2013
Data Process	Mediators Building Capacity		
Analytics Focus	Mediators Technology		
Vendor Awareness	Mediators Funding		

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Appendix G: Study 1 Description of Cluster Analysis Variable Categories

Table 4

Variable Category definitions

Variable Categories	Description
Concept Variables	The conceptualisations, constructions and understandings of different facets of learning analytics as well as phenomena distinct from, but related to, learning analytics
Readiness Variables	Concrete structures and tacets within an institution that may facilitate and mediate the implementation of learning analytics
Implementation Variables	Current and existing structures and conceptualisations that relate to, and exist in preparation for, or as a result of, learning analytics activity
Context Variables	Demographic institutional profile data

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Appendix H: Study 1 Cluster Analysis Medoids

Variables for each medoid, and therefore representations of each cluster, are presented below.

Table 5

Concept Variables

Domain Variable		LA Purpose	LA Driver Quantity	Type	Retent. Concep.	Learning Concep.	Dimension.	Data Interp.	Process	Analytics Focus	Vendor Aware.
ID	Cluster										
7	1	Measure	Multi.	Effic.	Indep.	Measure	UniDim.	Cons.	Induct.	AA+PA	N/A
26	2	Underst.	Multi.	Learn.	Inter.	Underst.	MultiDim.	Cons.	Induct.	AA+PA+LA	Recog.

Table 6

Readiness Variables

Variable		Leader. Structr.	Scope	Spons.	Strategy Develop.	Position	S-holder Consult.	Culture	Build. Cap.	Tech	Fund
ID	Cluster										
7	1	Distrib.	N/A	DVC	Interm.	Embed.	SM.	Acknow.	Recog.	Recog.	N/A
26	2	Distrib.	High	VC	Interm.	Embed.	Com.	Acknow.	Strat.	Strat.	Constr.

Table 7

Implementation Variables

Variable		Ethics	Stage	EDW	Scope	L Impact	Vendor Prod.	Evaluation
ID	Cluster							
7	1	Discuss.	Prep.	N/A	N/A	Aware.	No Vendor	Limited
26	2	Discuss.	Early	Comp.	Reten.	Action	Integrated	Recurs.

Table 8

Context Variables

Variable		Uni Group	State	City/Region	Enrolment	Retention 2012	Success 2013
ID	Cluster						
7	1	RUN	X	Regional	10756	71.25	80.72
26	2	IRU	X	Regional	10848	69.06	76.51

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Appendix I: Study 1 Cluster Analysis – Cluster Assignments

Table 9

Concept and Readiness Variables

Variable	ID	LA Purpose	LA Driver Quan.	Type	Retent. Concep.	Learn. Concep.	Dimens.	Data Interp.	Process	Analytics Focus	Vendor Aware.	Leadership Struct.	Scope	Spons.	Strategy Develop.	Position	S-holder. Consult	Culture	Build. Cap.	Tech	Fund
Cluster 1	1	Underst.	Multi	Effic.	Indep.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	Limit.	Decent.	N/A	DVC	None	Embed.	Senior M.	Acknow.	Recog	Strat.	Afford.
	2	Measure	Multi	Effic.	Indep.	Measure	Uni	Ess.	Induct.	AA+PA	Limit.	Distrib.	High	DVC	Interm.	Embed.	Senior M.	Limited	Strat.	Strat.	Afford.
	3	Measure	Few	Effic.	Indep.	Measure	Uni	Ess.	Deduct.	AA+PA+LA	Limit.	Central.	Low	DVC	None	Embed.	Comp.	Limited	Recog	Strat.	Afford.
	4	Measure	Multi	Effic.	Inter.	Measure	Uni	Cons.	Induct.	AA+PA	Recog.	Central.	N/A	DVC	None	Non	Senior M.	Acknow.	Recog	Strat.	Constr.
	5	Measure	Multi	Learn	Indep.	Measure	N/A	Ess.	Deduct.	AA+PA	Recog.	Central.	Low	VC	Interm.	Embed.	Senior M.	Acknow.	Recog	Recog.	Afford.
	6	Underst.	Multi	Effic.	Inter.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	N/A	Decent.	N/A	PVC	Interm.	Embed.	Senior M.	Acknow.	Recog	Recog.	Afford.
	7	Measure	Multi	Effic.	Indep.	Measure	Uni	Cons.	Induct.	AA+PA	N/A	Distrib.	N/A	DVC	Interm.	Embed.	Senior M.	Acknow.	Recog	Recog.	N/A
	8	Measure	Multi	Effic.	N/A	Measure	Multi	Cons.	Deduct.	AA+PA+LA	Limit.	Central.	N/A	PVC	None	Non	Senior M.	Acknow.	Recog	N/A	N/A
	9	Measure	Multi	Effic.	Inter.	Measure	Uni	Cons.	Deduct.	AA+PA	Limit.	Distrib.	N/A	DVC	Interm.	Indepen.	Senior M.	Acknow.	Recog	Recog.	Afford.
	10	Underst.	Multi	Effic.	Indep.	Measure	Multi	Cons.	Induct.	AA+PA+LA	N/A	Distrib.	Low	PVC	None	Embed.	Senior M.	Acknow.	Recog	Strat.	N/A
	11	Measure	Few	Learn	N/A	Measure	Multi	Cons.	Induct.	AA+PA+LA	Limit.	Distrib.	N/A	VC	None	Embed.	Senior M.	Acknow.	Recog	Recog.	N/A
	12	Measure	Multi	Effic.	Indep.	Measure	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Distrib.	N/A	DVC	Formal	Embed.	Comp.	Acknow.	Recog	Strat	N/A
	13	Measure	Multi	Effic.	Indep.	Measure	Multi	Cons.	Deduct.	AA+PA	Recog.	Distrib.	N/A	DVC	None	Non	Comp.	Strat.	Strat.	Recog.	Constr.
	14	Measure	Multi	Data	N/A	Measure	Uni	Cons.	Induct.	AA+PA+LA	N/A	Distrib.	Low	PVC	None	Embed.	N/A	Strat.	Strat.	N/A	Afford.
	15	Measure	Multi	Data	Inter.	Measure	Uni	Ess.	Induct.	AA+PA+LA	Limit.	Decent.	Low	DVC	Interm.	Embed.	Comp.	Limited	Recog.	Strat.	Constr.
Cluster 2	16	Measure	Multi	Learn	Inter.	Measure	Multi	Ess.	Deduct.	AA+PA+LA	Limit.	Central.	High	VC	Formal	Embed.	Comp.	Acknow.	Strat.	Strat.	Afford.
	17	Underst.	Few	Data	Inter.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Central.	Low	DVC	None	Indepen.	Comp.	Strategy	Recog.	Recog.	N/A
	18	Underst.	Few	Data	Inter.	Underst.	Multi	Cons.	Induct.	AA+PA+LA	Limited	Distrib.	Low	VC	None	Embed.	Comp.	Limited	Strat.	Strat.	Constr.
	19	Measure	Multi	Effic.	Indep.	Underst.	Uni	Ess.	Induct.	AA+PA	Recog.	Decent.	Low	VC	Interm.	Non	Comp.	Acknow.	Strat.	Strat.	Constr.
	20	Measure	Few	Learn	Indep.	Measure	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Distrib.	High	VC	Formal	Embed.	Comp.	Acknow.	Recog.	Strat.	Afford.
	21	Underst.	Multi	Learn	Inter.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Distrib.	High	VC	Formal	Embed.	Comp.	Strat.	Recog.	Recog.	Constr.
	22	Underst.	Multi	Learn	Inter.	Underst.	Multi	Cons.	Induct.	AA+PA	Recog.	Central.	High	DVC	Formal	Embed.	Comp.	Strat.	Strat.	Strat.	Afford.
	23	Underst.	Multi	Effic.	Inter.	Measure	Multi	Cons.	Induct.	AA+PA+LA	Recog.	Distrib.	High	VC	Formal	Embed.	Comp.	Acknow.	Strat.	Strat.	N/A
	24	Measure	Few	Learn	Inter.	Measure	Multi	Cons.	Induct.	AA+PA	Limit.	Central.	Low	DVC	None	Non	Comp.	Acknow.	Recog.	Strat.	Constr.
	25	Underst.	Few	Data	Inter.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Central.	High	DVC	Formal	Embed.	Comp.	Acknow.	Recog.	Strat.	Constr.
	26	Underst.	Multi	Learn	Inter.	Underst.	Multi	Cons.	Induct.	AA+PA+LA	Recog.	Distrib.	High	VC	Interm.	Embed.	Comp.	Acknow.	Strat.	Strat.	Constr.
	27	Underst.	Multi	Effic.	Inter.	Underst.	Multi	Ess.	Induct.	AA+PA+LA	Limited	Distrib.	Low	VC	Formal	Embed.	Comp.	Acknow.	Recog.	Recog.	Afford.
	28	Measure	Few	Learn	Inter.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Distrib.	Low	VC	None	Embed.	Senior M.	Strat.	Strat.	Strat.	Constr.
	29	Underst.	Few	Learn	Inter.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	N/A	Distrib.	N/A	DVC	None	Embed.	Comp.	Acknow.	Recog.	Recog.	N/A
	30	Measure	Multi	Learn	Inter.	Measure	N/A	Ess.	Deduct.	AA+PA+LA	Limit.	Decent.	N/A	VC	Interm.	Non	Senior M.	Limited	Limited	Strat.	Constr.
	31	Underst.	Multi	Learn	Indep.	Underst.	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Distrib.	High	VC	Formal	Indepen.	Comp.	Acknow.	Strat.	Recog.	Afford.
	32	Measure	Multi	Learn	Inter.	Measure	Multi	Cons.	Deduct.	AA+PA+LA	Recog.	Distrib.	Low	VC	None	Non	Comp.	Acknow.	Strat.	Recog.	Constr.

Table 10
Implementation Variables

Variable	ID	Ethics	Stage	EDW	Scope	L. Impact	Vendor Prod.	Evaluation
Cluster 1	1	Discuss.	Early	Limited	Reten.	Aware.	Integrated	Limited
	2	Limited	Early	N/A	Reten.	Reten.	Integrated	Limited
	3	Discuss.	Early	Limited	Reten.	Reten.	Integrated	Informal
	4	Policy	Early	Comp.	Reten.	Reten.	Integrated	Recurs.
	5	Discuss.	Early	Limited	Reten.	Reten.	No Vendor	Informal
	6	Discuss.	Prep.	N/A	N/A	Aware.	No Vendor	Limited
	7	Discuss.	Prep.	N/A	N/A	Aware.	No Vendor	Limited
	8	Limited	Prep.	N/A	N/A	Aware.	No Vendor	Limited
	9	Discuss.	Prep.	Limited	N/A	Aware.	No Vendor	Limited
	10	Discuss.	Early	Limited	Reten.	Reten.	No Vendor	Limited
	11	Discuss.	Prep.	N/A	N/A	Aware.	No Vendor	Limited
	12	Policy	Early	N/A	Reten.	Reten.	Integrated	Limited
	13	Limited	Early	Limited	Reten.	Reten.	No Vendor	Recurs.
	14	Discuss.	Early	Limited	Learn.	Action	No Vendor	Informal
	15	Discuss.	Prep.	N/A	N/A	Aware.	Vend. lead	Limited
Cluster 2	16	Policy	Prep.	Comp.	N/A	Aware.	No Vendor	Limited
	17	Discuss.	Prep.	Limited	N/A	Aware.	No Vendor	Limited
	18	Discuss.	Prep.	N/A	N/A	Aware.	Integrated	Limited
	19	Discuss.	Early	Limited	Reten.	Reten.	Integrated	Recurs.
	20	Discuss.	Prep.	Limited	N/A	Aware.	Vend. lead	Limited
	21	Discuss.	Prep.	Comp.	N/A	Aware.	No Vendor	Limited
	22	Policy	Early	Comp.	Reten.	Recursi.	No Vendor	Recurs.
	23	Discuss.	Advan.	Comp.	Learn.	Action	No Vendor	Recurs.
	24	Limited	Early	N/A	Reten.	Aware.	Aware.	Informal
	25	Policy	Early	Comp.	Reten.	Action	Integrated	Informal
	26	Discuss.	Early	Comp.	Reten.	Action	Integrated	Recurs.
	27	Policy	Prep.	Comp.	N/A	Aware.	No Vendor	Limited
	28	Discuss.	Early	N/A	Reten.	Action	Integrated	Limited
	29	Discuss.	Prep.	N/A	N/A	Aware.	No Vendor	Limited
	30	Limited	Prep.	Limited	N/A	Aware.	No Vendor	Limited
	31	Policy	Advan.	Comp.	Learn.	Recurs.	No Vendor	Recurs.
	32	Limited	Early	Comp.	Reten.	Action	No Vendor	Limited

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Appendix J: Study 1 Cluster Analysis Results

Table 11

Statistical difference between clusters for variables

	Variable	Test	Significance
Concept Variables	LA Purpose	X^2	P=.04048; significant
	LA Driver Quantity	X^2	Not significant
	LA Driver Type	X^2	P=.0025; significant
	Retention Conceptualisation	X^2	P=.0025; significant
	Learning Conceptualisation	X^2	P=.0055; significant
	Learning Dimensionality	X^2	P=.01699; significant
	Data Interpretation	X^2	Not significant
	Data Process	X^2	Not significant
	Analytics Focus	X^2	Not significant
	Vendor Awareness	X^2	Not significant
Readiness Variables	Leadership Structure	X^2	Not significant
	Leadership Scope of Influence	X^2	P=.009; significant
	Leadership Sponsorship	X^2	P=.0035; significant
	Strategy Development	X^2	P=.03898; significant
	Strategic Position	X^2	Not significant
	Stakeholder Consultation	X^2	P=.0015; significant
	Culture	X^2	Not significant
	Building Capacity	X^2	P=.04848; significant
	Technology	X^2	Not significant
	Funding	X^2	Not significant
Context Variables	University Group	X^2	Not significant
	State	X^2	Not significant
	City/Region	X^2	Not significant
	Student Enrolment	F	Not significant
	Retention 2012	F	Not significant
	Success Rate 2013	F	Not significant
Implementation Variables	Ethics	X^2	Not significant
	Stage	X^2	Not significant
	EDW	X^2	P=.02999; significant
	Scope	X^2	Not significant
	Learning Impact	X^2	Not significant
	Vendor Product	X^2	Not significant
	Evaluation Process	X^2	Not significant

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Appendix K: Study 1 Summary of Differences

Table 12

Summary of variables on which Cluster 1 and Cluster 2 differed significantly

Concept Variables	Readiness Variables	Implementation Variables
LA purpose	Leadership scope of influence	Enterprise data warehouse
LA driver type	Leadership sponsorship	
Retention conceptualisation	Strategy development	
Learning conceptualisation	Stakeholder consultation	
Learning dimensionality	Building capacity	

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Appendix L: Study 1 Cluster Analysis Readiness Variables

Table 13

Readiness Variables of Institutions in Preparatory Stage of Implementation

Variable		Leadership Struct.	Scope	Spons.	Strategy Develop.	Position	Stakehold. Consult.	Culture	Bld. Cap.	Tech	Fund
	ID										
Cluster 1	6	Decent.	N/A	PVC	Interm.	Embed.	Senior M.	Acknow.	Recog	Recog.	Afford.
	7	Distrib.	N/A	DVC	Interm.	Embed.	Senior M.	Acknow.	Recog	Recog.	N/A
	8	Central.	N/A	PVC	None	Non	Senior M.	Acknow.	Recog	N/A	N/A
	9	Distrib.	N/A	DVC	Interm.	Indepen.	Senior M.	Acknow.	Recog	Recog.	Afford.
	11	Distrib.	N/A	VC	None	Embed.	Senior M.	Acknow.	Recog	Recog.	N/A
	15	Decent.	Low	DVC	Interm.	Embed.	Comp.	Limited	Recog.	Strat.	Constr.
Cluster 2	16	Central.	High	VC	Formal	Embed.	Comp.	Acknow.	Strat.	Strat.	Afford.
	17	Central.	Low	DVC	None	Indepen.	Comp.	Strategy	Recog.	Recog.	N/A
	18	Distrib.	Low	VC	None	Embed.	Comp.	Limited	Strat.	Strat.	Constr.
	20	Distrib.	High	VC	Formal	Embed.	Comp.	Acknow.	Recog.	Strat.	Afford.
	21	Distrib.	High	VC	Formal	Embed.	Comp.	Strat.	Recog.	Recog.	Constr.
	27	Distrib.	Low	VC	Formal	Embed.	Comp.	Acknow.	Recog.	Recog.	Afford.
	29	Distrib.	N/A	DVC	None	Embed.	Comp.	Acknow.	Recog.	Recog.	N/A
	30	Decent.	N/A	VC	Interm.	Non	Senior M.	Limited	Limited	Strat.	Constr.

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Appendix M: Study 2 Cluster Analysis Statements

Expert panel responses to the prompt:

For learning analytics to make a continued impact on learning and teaching it would need to…

Table 14

Cluster Statements

Cluster	Statements
1. Data platform: standards and governance	1. be very widely implemented in an ecosystem that shares data 7. guarantee the security of the data 12. be standards-based and technology platform agnostic 13. make "openness" a priority so that models, data, and best practices can be shared across institutions 16. make clear if third parties will get access to the collected data at any point 39. have policies on ethical use of data and effective systems of data governance in place first 49. not be dependent on technologies that are likely to be replaced or quickly become obsolete 64. have standards for comparison across instances, institutions, etc. 66. be cloud based 70. recognise the distributed architecture of interactions and not attempt to force things into a single database 71. be able to capture data from all sources and collect this data in a single repository
2. Data use: accessible, transparent, valid/reliable	8. make clear how confident any predictions about student success/failure are, and why those predictions are being made 19. produce results that are presented in such a way that the end users can drill down to the raw data so that validity can be checked 21. allow students to delete any optional/personally supplied information 26. be available on mobile platforms 35. be evaluated for generality so that the contexts in which they can be used reliably are known -- it's important to guard against invalid application 43. make its research reproducible through references datasets, shared models etc. 44. be easy to access and use 48. be transparent about the use of data points and applied algorithms 60. ensure that analytic tools should only be used by people with enough understanding of how they work so that the results can be treated with an appropriate level of skepticism 74. develop a theoretical and conceptual foundation that unifies research from many disciplines interested in learning and teaching

3. Compatibility w-existing values/practices/systems	4. be deployed in a systemic manner with the needs of varying stakeholders accounted for 11. practical and implementable, e.g. not just narrow research but lending itself to system/program design and delivery 15. align with organisational design 31. enable implementation that recognises the complexity of educational systems 38. be implemented bottom up 40. engage all stakeholders involved in teaching, learning, and governance of educational systems 53. be accepted as a standard of practice 54. transform organisational design 59. be deployed in a systemic manner with the needs of varying stakeholders accounted for 4. Strategy: whole-of- organisation view 5. be available as a service that works with the institution's other student systems 9. have implementation that recognises need for cross-institutional understanding, skills upgrades, and acceptance 24. have central investment 37. be facilitated through a enterprise-wide system rather then software-centric solutions 41. start with an institutional capability assessment encompassing dimensions such as institutional risk appetite, faculty perceptions, student consultation, data quality audit and technical capability 50. have complete support and recognition from the institution's senior leadership 57. demonstrate value (ROI) to institutions that do not have retention or performance issues 65. be integrated into the long term planning that drives the institution 67. meet identified institutional needs
4. Strategy: whole-of-organisation view	5. be available as a service that works with the institution's other student systems 9. have implementation that recognises need for cross-institutional understanding, skills upgrades, and acceptance 24. have central investment 37. be facilitated through a enterprise-wide system rather then software-centric solutions 41. start with an institutional capability assessment encompassing dimensions such as institutional risk appetite, faculty perceptions, student consultation, data quality audit and technical capability 50. have complete support and recognition from the institution's senior leadership 57. demonstrate value (ROI) to institutions that do not have retention or performance issues 65. be integrated into the long term planning that drives the institution 67. meet identified institutional needs

5. Actionable tools with an evidential base	2. demonstrate empirical impact on student success 10. be able to accommodate multiple levels of sophistication of students and teachers as 'users' 22. minimise workload through simple visualisations available to both faculty and students 28. provide evidence of high improvements in learning experiences 29. develop tools and algorithms that provide real time comprehensive feedback to students 34. be clear and critical in the ways in which it conceives of 'student success' 61. account for the human dimensions of analytics, not only Artificial Intelligence/Machine Learning models 62. produce reports/displays that are actionable by educators and students only inform and not make decisions from an algorithm without 69. human evaluation (danger of creating a data driven self-fulfilling prophecy education system)
6. Supporting student empowerment	3. help learners understand their learning rather than pointing out what they are doing wrong 14. be focused on providing learners with data and information to self-regulate their own learning 18. be judged useful by learners 30. create awareness about other learning practices and social networks around them that they can use to make to meaningful connections 32. used in a supportive manner (support student and teacher daily work) rather than a business analytics manner 51. support personalised learning strategies 52. help learners keep track of the effects of their experiments on their learning in which "treatments" are changes they make to tactics used in learning 55. involve students in the design and validation of new tools, possibly with pedagogical benefits to the students 6. blend with proven best practice 17. be co-designed with educators who understand what good learning looks like in their field 20. be flexible enough to encompass diverse teaching practices 23. be integrated in daily learning events 25. be recognised as crucial to research in teaching and learning 27. motivate faculty to make a change in their pedagogy because the evidence of impact on student learning is clear 33. be recognized as valuable by those who do teaching (instructors, instructional designers, curriculum committees) 36. reflect the complexity and multi-dimensionality of teaching and learning practices 42. provide feedback to all stages of the learning process (design, dean, teacher, gov't officials, learner, etc) 45. be driven by pedagogy 46. be integrated with the work practices of educators 47. provide educators with formative feedback which helps them improve their practice

	56. be integrated into the environments, practices and processes of teachers and students 58. address the problems and requirements experienced during learning and teaching, rather than those of institutions and researchers 63. advance pedagogies that educators value 68. be able to respond to changes in learning and teaching practices 72. offer rewards for use to students and teachers that overcome inherent inertia and resistance 73. use formative feedback based rewards for staff (rather than summative performance indicators with penalties)

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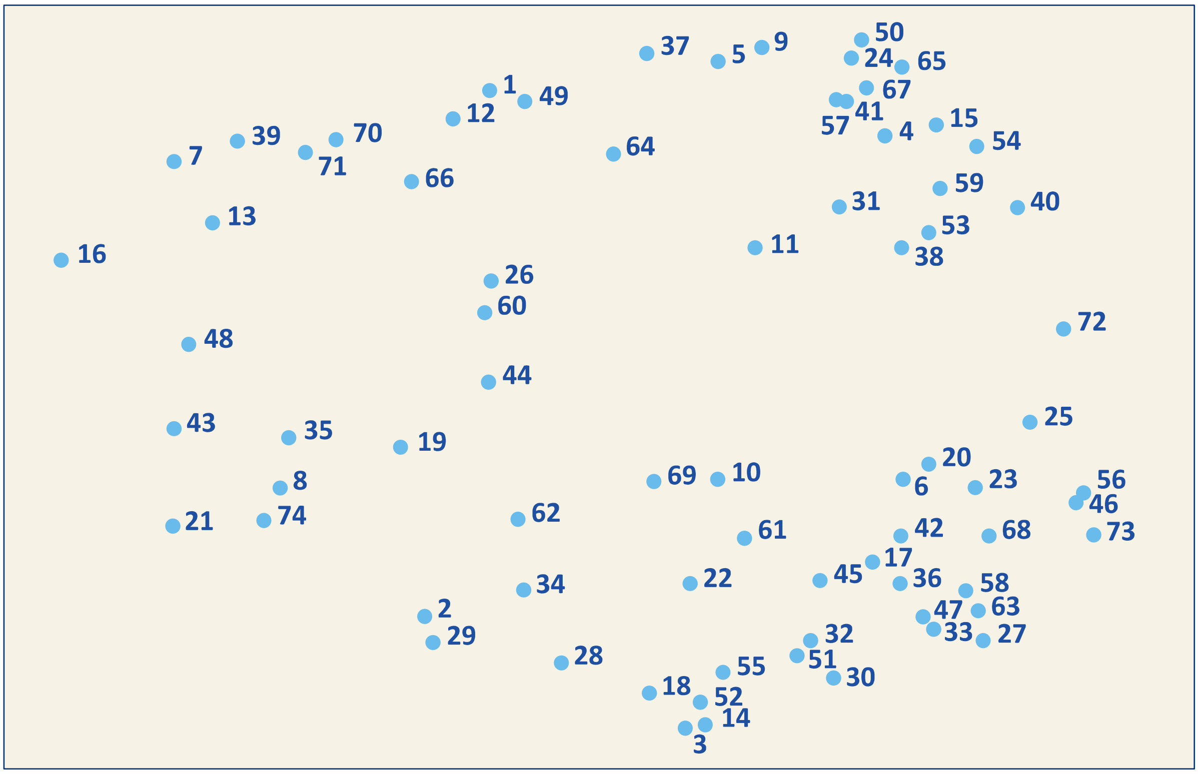
Appendix N: Study 2 Cluster Analysis Point Map

A multidimensional scaling arrayed the expert panel's statements as a two-dimensional point map. Figure 7 illustrates the point map with the statement numbers. The final stress value of this analysis was 0.2592, well within the bounds that indicate the goodness of fit of the configuration [69].

A number of cluster solutions were produced using the point map as the basis. The investigators considered the range of plausible final solutions likely to fall between 5 and 16 clusters, based on both conventions of previous research and on the pragmatic requirement to provide enough detail to guide decision makers and implementers. The implications of this choice can be illustrated through a comparison of the lowest solution possible, two clusters (Appendix O), with the seven-cluster solution that constituted the final selection (Appendix P).

Figure 7: Cluster Analysis Point Map with Statement Numbers



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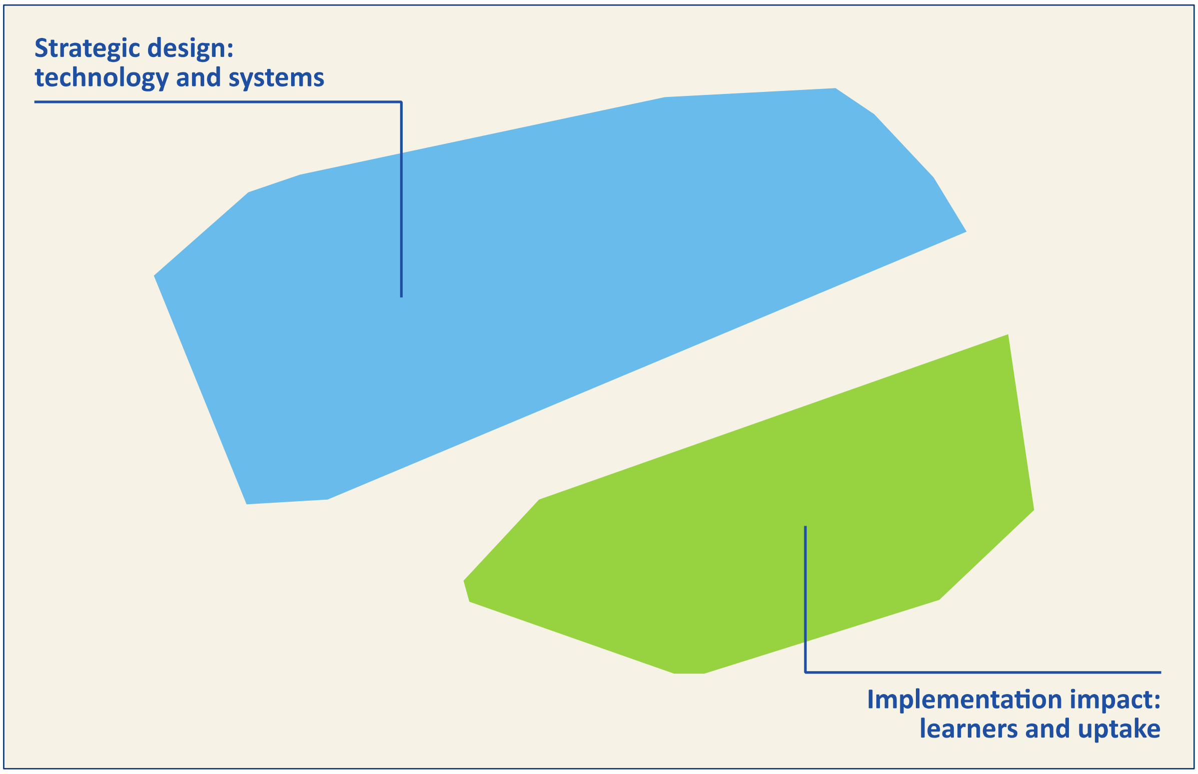
Appendix O: Study 2 Two Cluster Solution

This solution in Figure 8 aggregates the collective sorting decisions of the expert participants into a *Strategic design: technology and systems* cluster or an *Implementation impact: learners and uptake* cluster. That is, the expert participants saw the two overarching drivers for long-term impact for learning analytics as:

1. the setting of a strategic direction and the development of supportive conditions
2. the deployment of impactful implementation mechanisms that motivate sustained uptake.

While this is an important thematic finding in its own right it is not sufficiently detailed to give insight or guide action. After a thorough inductive analysis that examined more granular groupings of the underlying statements, the investigators arrived at the seven cluster solution shown in Appendix Q.

Figure 8: Two Cluster Solution



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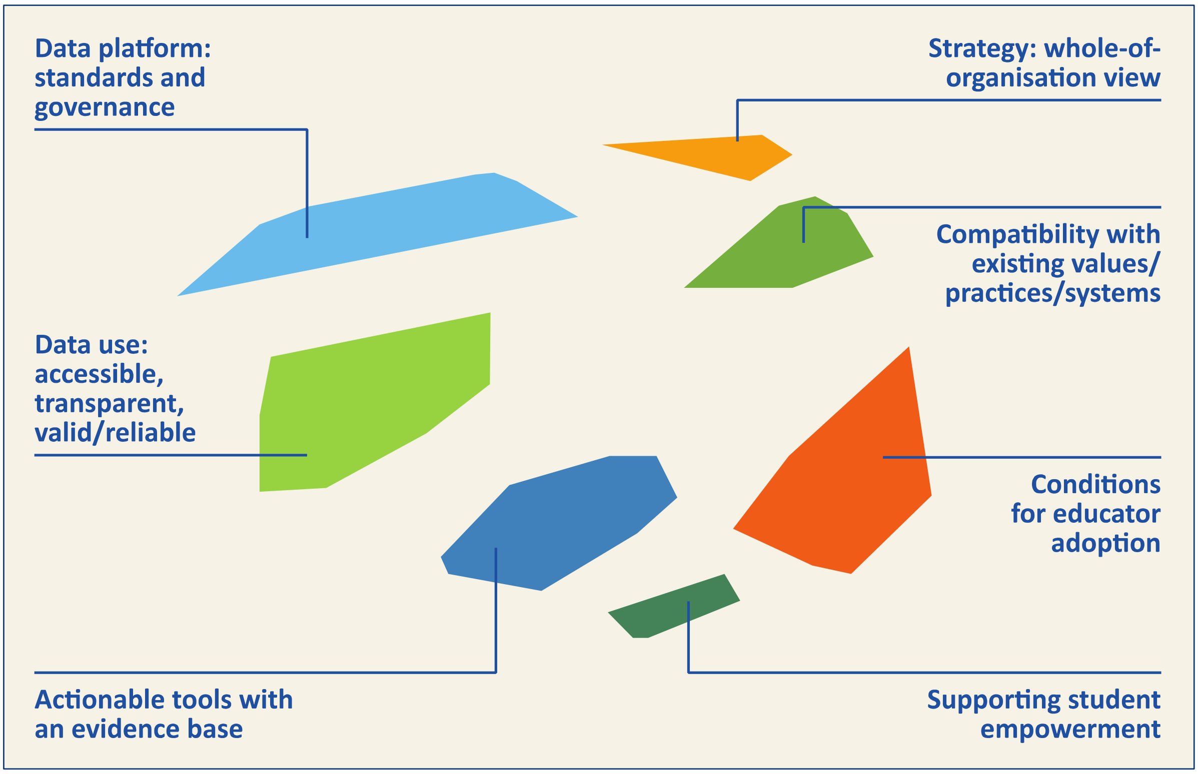
Appendix P: Study 2 Seven Cluster Solution

Figure 9: Seven cluster solution



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Appendix Q: Study 2 Cluster Analysis – 7-cluster Solutions with their Functions and Categories

Table 15

Study 2 Cluster Analysis: Mapping between the 2-cluster and 7-cluster analyses, with their functions and example statements

Clusters	Example statements *For learning analytics to make a continued impact on learning and teaching it would need to…*
Strategy: whole-of-organisation view	• have complete support and recognition from the institution's senior leadership • be integrated into the long term planning that drives the institution • have central investment • be facilitated through a enterprise-wide system rather than software-centric solutions
Compatibility with existing values/practices/ systems	• be deployed in a systemic manner with the needs of varying stakeholders accounted for • engage all stakeholders involved in teaching, learning, and governance of educational systems • align with organisational design
Data platform: standards and governance	• guarantee the security of the data • have policies on ethical use of data and effective systems of data governance in place first • be standards-based and technology platform agnostic • be very widely implemented in an ecosystem that shares data
Data use: accessible, transparent, valid/reliable	• be easy to access and use • be transparent about the use of data points and applied algorithms • make its research reproducible through references datasets, shared models etc. • be evaluated for generality so that the contexts in which they can be used reliably are known -- it's important to guard against invalid application
Actionable tools with an evidential base	• demonstrate empirical impact on student success • produce reports/displays that are actionable by educators and students • minimise workload through simple visualisations available to both faculty and students
Conditions for Educator adoption	• be recognized as valuable by those who do teaching (instructors, instructional designers, curriculum committees) • be co-designed with educators who understand what good learning looks like in their field • be integrated with the work practices of educators • advance pedagogies that educators value • offer rewards for use to students and teachers that overcome inherent inertia and resistance

Clusters	Example statements *For learning analytics to make a continued impact on learning and teaching it would need to…*
	• provide educators with formative feedback which helps them improve their practice
Supporting Student empowerment	• be judged useful by learners • be focused on providing learners with data and information to self-regulate their own learning • support personalised learning strategies • create awareness about other learning practices and social networks around them that they can use to make to meaningful connections

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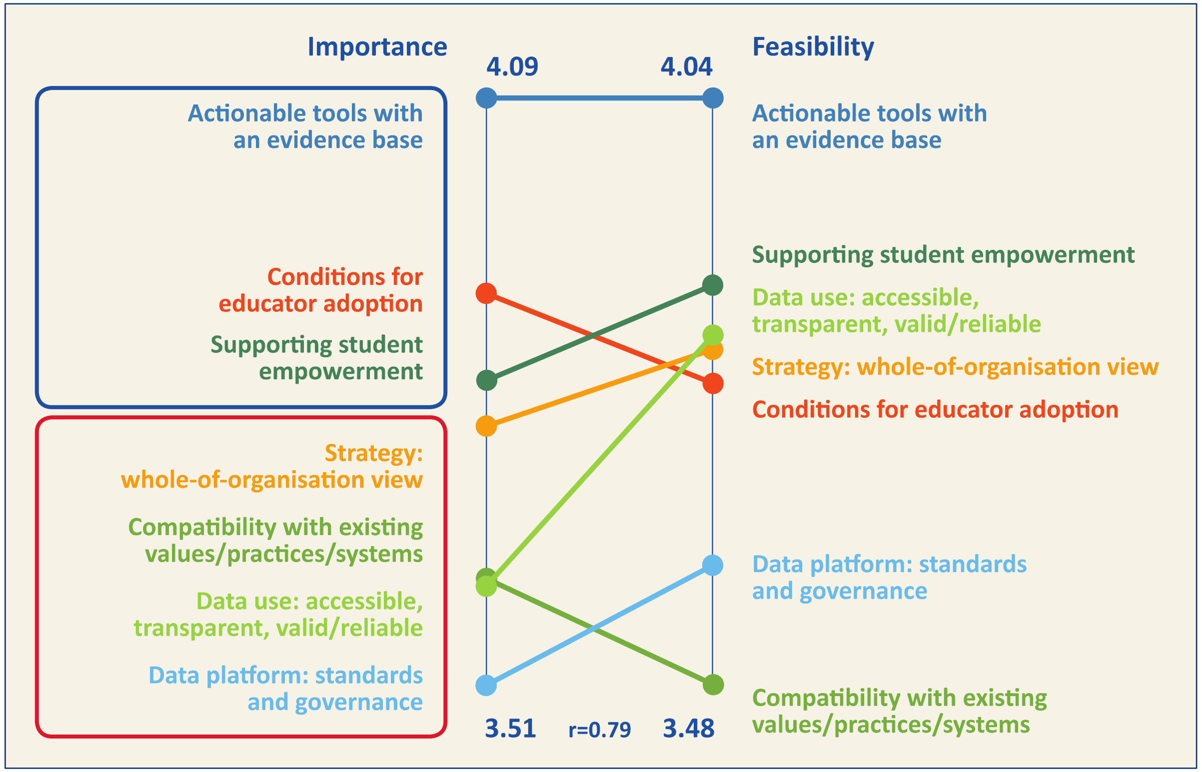
Appendix R: Study 2 Cluster Level Pattern Match

Figure 10: Pattern Match at Cluster Level for Importance and Feasibility Scales



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Appendix S: Study 1 Coding Protocol

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
Concept	LA Purpose	Measure	1	The primary purpose of learning analytics is to measure a phenomenon (i.e. student learning, student engagement, student performance, student retention). More emphasis appears to be on using learning analytics for measurement, reporting and/or using outcomes as opposed to understanding the processes, antecedents and possible mediators that may be shaping them. There may be a reference to understanding, but this will be brief and not explained.	[46, 50, 57, 58]	"And so I think of it as being useful data that provides the evidence that we need to, to be able to measure for achieving our objectives for teaching and learning. So basically we have a set of objectives around outcomes for our students and, and, and the, and the experience that we wish to provide for them. And we use data to help us measure whether we've achieved that or not." (29134)
		Understand	2	The primary purpose of leaning analytics is to understand a phenomenon (i.e. student learning, student engagement, student performance, student retention). More emphasis appears to be on using learning analytics to understand and provide insight into the processes, antecedents and possible mediators that may be shaping outcomes.		"We have written into our new strategic plan using learning analytics to improve the learning outcomes and our understanding of our students learning and we think that is the right way to go." (29138)
	LA Driver Quantity	Limited	0	The participant cites only 0-1 explicit, externally-generated motivation(s) for the implementation of learning analytics. Drivers can include a desire to increase retention, or improve learning outcomes.	[3, 4]	"Um I think it's about using data to maximise um student success… Student success in, in their learning, so identify students at risk but also enable students to ah track their own performance, look at themselves in relation to their peers. Also enable staff to monitor their own teaching, enhance their own teaching as a consequence of the learning analytic feedback. So it's really um, so you can maximise student's success as a teacher by um enhancing your own teaching as a consequence of the feedback you receive through learning analytics." (32254)
		Few	1	The participant cites 2 explicit, externally-generated motivation(s) for the implementation of learning analytics.		"And the benefit is that you can actually see over time if you're achieving what you set out to achieve, because this, because the goals that we've set for student learning are not goals that can be achieved within a year… I think we have a particularly challenging student cohort and so we've set, and we've had to advisedly set challenging goals for retention and completion" (29134)

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
		Multiple	2	The participant cites 3 and above externally-generated motivation(s) for the implementation of learning analytics.		“So it is to increase retention and completion. Also to, you know, possibly increase the positive experience that a student might have. So I'd say learning analytics are going for a more personal note. But there's no reason why they can't also have a broader band for the units, for subject improvement. You know, how students are working with particular items. You know, particularly as we've invested so much in online, trying to improve our online presentation material. And analytics of that usage hopefully will maybe show us that, whether it's good bad or indifferent.” (29132)
	LA Driver Type	Efficiency	0	In addition to drivers of student success, learning and retention, learning analytics activity is driven by performativity and efficiency objectives of the institution, such as quality assurance and resource efficiency.	[13]	“It's essentially about, um, providing, maximising our allocation of resources. We actually don't have huge amounts of additional resources that we can just throw around.” (29136)
		Data efficiency	1	In addition to drivers of student success, learning and retention, learning analytics activity is driven by a priority to use student data effectively and comprehensively in order to meet institutional goals.		“And I think sitting back inside our own institution and thinking of the data that we use and how we use it, um, the benefits are that I suppose when I, you know, but if I’m thinking about learning analytics I’m probably thinking that we are using whole of institution data more wisely and um, than we’ve been able to do in the past, and certainly hope to be a-, and, and expect to be able to do it even better in the future, and that um, and, and we, in our case I think we’ve really shifted to a whole, a coherent whole of university approach” (29134)
		Learning and/or student success	2	Drivers for learning analytics activity are focused primarily on increasing student learning and success, with little or no mention of efficiency drivers.		“So from our perspective the benefits are that we can create, um, more appropriate, more responsive and better quality learning experiences for our students. So that we can design their courses, um, in a way that facilitates their learning most effectively. And I would probably also say most efficiently.” (29131)
	Retention Conceptualisation	N/A	0	There is insufficient reference to retention to determine how it is conceptualised.	[32]	
		Independent	1	Retention is conceptualised as a stand-alone activity and proximal outcome, with a focus on prediction and identification of risk factors (such as demographic variables and engagement behaviours) and intervention. There is no discussion or identification of teaching and learning and/or student capital antecedents to retention.		“With some of our key um, goals around student retention and completion for example, which are really important goals for this university… we’ve had to advisedly set challenging goals for retention and completion… We’ve got a project focusing on first year, um, retention and completion, and that’s one of the most significant strategic projects in the university, because we have such, you know, about 90% of our students, of our higher education students are undergraduate students, and the retention from the first year to the second year is probably the most, one of the most critical p-, um, aspects of, of our work. And we, we used two types of data um, in our retention strategy. Um, one we, we use a set of quantitative measures based on um, indicators of success, so we use um, well benchmarked

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
						and researched indicators to, as um, to provide um, us with information about students who are likely to withdraw. And those, those students are pr-, are identified and provided with um, particular support, targeted support that's um, intended to um, max-, optimise the chance that they'll remain in the university and, and, and complete the first year of their degree and progress into second year. We also use a set of qualitative triggers which rely on, on academic staff identifying um, oh sorry, academic staff are trained, um, to observe and, and report those triggers and then, and then students that are, that are behaving, and they're based on student behaviours so where, you know, missing classes, get, handing assignments in late, that sort of thing." (29134)
		Inter-dependent	2	Retention is conceptualised as a distal outcome, shaped and influenced by a range of intersecting antecedent factors, including teaching and learning and/or student capital.		"We certainly care about… the sort of social analytic side the part that suggests that there are things outside of academic performance that we're seeing that are responsible for a significant proportion of attrition statistics. And we'd like to be able to situate that with data around the individual's engagement with the university because our traditional measures of academic success aren't indicating that these people are at risk. Nevertheless they are, so there's two possibilities. One is, is that our academic indicators are not sufficiently nuanced to be able to catch trends or patterns that matter with the crudity that were currently looking at it. And secondly that there is a combination of those factors with other factors that we might be able to pick up that would help us." (29138)
	Learning Conceptualisation	N/A	0	There is insufficient reference to learning to determine how it is conceptualised.	[53, 58, 59]	
		Measure	1	Learning is conceptualised primarily as a behaviour or indicator to be measured.		"So we use learning analytics to optimise students' learning through the capture, analysis and reporting of data about the learners and their contexts." (29133)
		Understand	2	Learning is conceptualised primarily as a phenomenon to be understood. Measurement can be incorporated in this conceptualisation. Evidence of a desire to modify curriculum suggests that learning is something to be understood.		"A lot of folks might think in terms of traditional institutional analytics um, versus what I would think of as being learning analytics, um, would ah, get more into ah, the details of ah, student, ah, ah, student learning, motivation, success um, and into how students are interacting with ah, ah, with different resources… Um, well it would be nice to be able to say um, ah, the, here are things that um, that will be more um, more or less effective for addressing different ah, ah, learning needs and not just because we say so, but because we've looked." (29145)
	Learning Dimensionality	Not stated	0	There is insufficient reference to learning to determine dimensionality.		

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
		Uni-dimensional	1	Learning conceptualised through a very limited single lens, typically one lens only (i.e. personalised learning, motivation, self-regulation) but a second can be referred to briefly.		"Um, I think learning analytics is the use of, um, data, um, in an intelligent way to understand the effectiveness of your current assessment practices, um, to try and identify ways in which those assessment practices can be modified to provide better learning outcomes for students." (29481)
		Multi-dimensional	2	Learning is conceptualised through multiple (that is two or more) lenses.		"We were trying to develop this sort of expert system for teaching and learning where you had a, a model that was about the content that was being learned, a model that was about pedagogy, and a model about the student. And so we were trying to write programs that would say, "For this student learning this content, this is the best pedagogical approach to take." (32256)
	Data Interpretation	N/A	0	There is insufficient discussion of data to determine interpretation.	[5, 46, 60]	
		Essentialist	1	Data is the end product with no need for interpretation; data is the truth. There is a focus on 'what' the data reveals with very little evidence of understanding the 'how' or 'why' behind the data.		"So we use learning analytics to optimise students' learning through the capture, analysis and reporting of data about the learners and their contexts. And then we have a particular focus on near real time provision of analytics to the students and the teachers when they're in their learning context." (29133)
		Constructivist	2	It is acknowledged that a deeper understanding requires interpretation of the data; data is used as a lens. There is a focus on 'how' or 'why' the findings came to be. Institutions coded 'constructivist' can also demonstrate examples of essentialist interpretation in addition to instances of 'constructivist' analysis.		"So, you know, I mean, we seem to be, we seem to be living in such a massive amount of data. It's actually trying to cut through and think, well what's the important stuff? Which? Should we stop asking people and wasting their time? What's the most valuable data to collect, and how we use it? If that makes sense." (29132)
	Data Process	N/A	0	There is insufficient discussion of data to determine process.	[34, 61]	
		Inductive	1	Learning analytics activity is driven by the data collected. The investigation is secondary to data collection.		"So at this stage I don't think that we really are doing much in the area of learning analytics. We are doing quite a bit of work in what I would call business intelligence which is using data that we can glean from our system, um, about, um, student's performance, student engagement and so on, but really, um, in an effort to use it as a trend starter and perhaps to inform where there are issues that we need to address. And one of the clear areas that we would, um, would be interested in using that data is in the area of student retention." (29140)
		Deductive	2	There is evidence of deliberate and strategic collection of data to answer specific, predetermined questions. The aims of the investigation inform the approach and the type of data that is collected.		"I'm a cognitive psychologist so I can, you know so the learning process is really something I understand and I can frame the right to questions or some of the right questions there…because I think we'll have the expertise and about what to collect, why to collect it and how, you know sort of how we go about it" (29131)

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
	Analytics Focus	Academic analytics	0	Type of analytics employed or planned to be employed are primarily academic, in order to assess institution performance (i.e. learner profiles, teaching quality, course quality, resource allocation and efficiency)	[62]	"So with the academic sort of learning analytics um, yes we've of course been measuring through progression, retention, um surveys, that sort of thing, um for a long time." (29131)
		Academic and predictive analytics	1	There is evidence of both academic and predictive analytics, employed or planned to be employed to assess institution performance and support retention goals		"By better understanding when they're at risk and being able to intervene in a timely manner. Um, and possibly also more predictive models about the, even selection of students. The kind of ah, criteria that ah, might predict later performance… We have an office of transition, which is where it's happening. But it's, it's a funded project with, ah, data modelling people and a call centre, basically. Who do the intervention… We're profiling all commencing students and giving them a risk rating. And calling them from worst risk, ah, upwards." (29137)
		Academic, predictive and learning analytics	2	There is evidence of academic, predictive and learning analytics (i.e. learning experience design, social networks, conceptual development, language analysis) employed or planned to be employed in order to assess institution performance and support retention, whilst also supporting learning		"So we used um, data mining to um, to develop a, a list of stu-, first year students who were most at risk of attrition, and we focused our telephone calls on calling those… Another project is, I discovered by accident, um, that we have some subjects that we called "killer" subjects; that's subjects that have pass rates in the teen… So we actually used um, again, analytics to, to look at what the factors were that might be contributing to that high failure rate, and then we, we tackled those issues and now um, the pass rate's gone up…one of the things that I think we're probably, we've sort of agreed on already is um, sort, sort of discourse analysis with the per-, with the aim of providing students automated feedback on their work." (32256)
	Vendor awareness	N/A	0	There is insufficient discussion to determine perception of vendor(s) or vendor products.		
		Limited awareness	1	Very limited to no recognition of potential constraints or limitations associated with using an external vendor or vendor product for analytics. If a limitation is mentioned, it is in passing and not discussed. This coding does not relate to attitudes to vendors or vendors' products per se (these can be positive or negative).		"I understand they're not that good. I mean I've heard so many things about them, I will have a look one day but I believe that they're not um, they're not going to be appropriate for everything that we need. But, yeah I am very aware that there are modules. I don't think people are using them very much at all. We've done many sort of surveys of our teachers about Blackboard over the years and that one doesn't come up very much." (29131)
Readiness	Leadership Structure	Decentralised	0	There is very little, or no, evidence of centralised leadership.	[48, 49]	"Um, to say that we have a comprehensive Institution wide Learning Analytics initiative we would probably be overstating it but there's various office's that are doing some work and we're trying to pull it all together a little bit in a little bit more of a systematic way." (29139)
		Centralised	1	Learning analytics driven by top-down leadership from a limited number of sources. This is a predominately vertical and		"It came top down from, from the central administration. But from, from, myself and the vice-chancellor's group, we discussed it. And then it's been administered centrally by planning services and transition

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
				hierarchical model.		office. The faculties and schools have been kept informed and they're, there is a reference group that I chair, which just basically looks at our entire first year and transition experience, so they have been, of the projects they have been looking at, it's very much and quite consciously top down." (29137)
		Distributed	2	While learning analytics is still centrally 'controlled' there is evidence that the organisation is pursuing a distributed leadership model. Resources are provided and structures developed to enable staff to take leadership in their areas of influence. There is evidence of 'bottom-up' leadership across multiple, often interacting, sources.		"It's likely that they would, that those faculties will be building out resources at their level with whom we can engage. So I think that the notion that this is entirely driven by the, by the Centre and the top down is not a scalable model. It's got to be a partnership that has direction and strategic um guidance from, ah from the central units but in implementation reality it is got to be a patchwork of connections with faculties and schools." (29138)
	Leadership Scope of influence	N/A	0	There is insufficient discussion of leadership to determine the scope of influence, or insufficient leadership demonstrated as per criteria listed below.	[34, 50, 67]	
		Low	1	With regard to the leader(s) of learning analytics activity, there is evidence of 2 of the following behavioural criteria OR, if 3 or more criteria observed, but criteria (1) is absent: (1) Securing organisational mandate and support for learning analytics agenda; (2) Monitoring and awareness of learning analytics activity in the field; (3) Fostering an organisational culture that is positive about and receptive to the use of learning analytics; (4) Fostering agency through provision of learning analytics resources and training to empower staff; (5) Development and implementation of learning analytics strategy consistent with institution goals		"Ah, yes there are real time analytic groups. Um there's one… in the Engineering Faculty has a, um a group working on um, real time analytics. Um, so there's one or two sort of areas that I couldn't, you know I'm not that familiar with but I know that they're going on. Ah, so but it is not a whole, for real time stuff it's not a whole of university thing at all… So we have just um, um welcomed on board a new DVC... So in, at the moment, I mean she's only just been here two weeks but she has already suggested to me, anyway, I don't know who else but she will be having an analytics team in the portfolio, in her portfolio... And, I've you know, I've kind of, well I would say I've been driving it, I haven't been, I haven't actually been doing anything but I've been, well apart from these reports I've taken it upon myself to do, but the need for, you know leadership in this area is, you know has been pressing." (29131)
		High	2	Evidence of a very high level of influence. Demonstrated 3 or more of the above criteria, one of which is criteria (1)		"Another part of our analytic strategy is that we think there's no point in collecting a lot of data um, and bringing different data sets together and doing analysis if people don't understand enough about statistics to know what it means. So we have um, a whole project to improve the numeracy of our staff and students, so we developed a formal aware subject and we've been piloting it with academic staff…But I've sort of been watching it in the background all along, and then about 2011, 2012 I started reading some things that George Siemens was writing, um, and I'd been, the, the, the main trigger…I started this a couple of years ago and started it with an all day workshop um, that

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						staff at all levels came to and were very engaged with, you know, from the Vice Chancellor down. That's when we brought George out. And there was quite a lot of buy-in right from the start. Um, I mean there's a lot, there's, we've got all sorts of committees now, sort of governing and they're all very keen and very excited about it…I mean I had to do a lot of talking to the then Vice Chancellor um, and my colleagues, but the new Vice Chancellor was one of my colleagues and he has completely bought into it (32256)
	Leadership Sponsorship	PVC (0) /DVC (1) /VC (2)		Level of sponsorship for learning analytics.	Inductive	
		Recognised	2	Recognition of possible constraints associated with employing an external vendor or vendor product. Limitations are (briefly) discussed. Participants can be positive to vendors and vendor products while also cognisant of their limitations.		"And I like vendors and I like software companies, so I'm not an anti-commercial person but I think in terms of learning analytics if there isn't a more open learning analytics push we'll end up in a world where all of our data is siloed into these separate analytics systems. And we will also not ourselves know how some of these are working, so I think we could find ourselves at a point where a student comes to you and says listen I got this alert, I got an intervention saying I was not doing well, why? What made the prediction tell you that? And if the answer is you know I can't tell you because our vendor won't tell us. I don't think that that's gonna be an answer people accept. Or your academic analytics dashboard saying you need to invest more money in tutors. Your provost is going to say okay, how'd that happen? What's the behind that prediction? And if you're not able, oh just trust the vendor. That's not gonna work." (28580)
	Strategy Development	None	0	There is recognition of the need for, yet no development of a formal strategy for the implementation of learning analytics to date.	[63, 64]	"We have an initiative, but our initiative at the moment is to develop a strategy." (29135)
		Intermediate	1	There is evidence of a formally developed strategy, although it does not have universal reach. It may be nascent, emerging, or involve a pilot.		"But the learning, the um, analytics that we're using in our work with [vendor] as part of our first year experience strategy, I mean that came out of my area of the university that was, grew out of a project that I made a fairly, you know, that we decided to pilot last year and, so it's something that's kind of grown like topsy. I mean this year the council are really enthusiastic about it and want to see it, and, and supported it being rolled out. And the um, the analytics that are part of the um, learning management system are also being managed out of my part of the university. Though having said that, we're making sure that we're talking to planning and also to the systems people to make sure that we do have a joined up approach. But certainly there isn't a single point of accountability for all analytics at the moment." (29134)

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
		Formal	2	There is evidence of a formally developed strategy for whole of university. When two strategies are evident, the highest strategy will be coded.		"We have a learning analytics strategy, and it's unfolding as we speak. It's been going since, um, uh, August last year. And at the beginning of the Spring session this year we will have near real time provision of analytics to teachers and students available, using the solution that we've developed. The sponsorship came from the deputy vice chancellor education. She appointed a director of business analysis and learning analytics. Then the person in that role collaborated with senior academic staff in all of the faculties, academic development staff who work in the learning and teaching unit in the centre in the institution. And, um, following that collaboration a draft was developed. It went back out for further consultation. Then it went to, um, the vice-chancellor's advisory group for endorsement because it's got resourcing requirements attached to it, and so the first, um, step once you've drafted something like this is to get the senior executive at the institution to support it. And a presentation was made to them, and they supported it. Um, then it went to the university education committee for further comment and endorsement, and that occurred. And then the strategy started to unfold… So, the first action was to establish a learning analytics governance arrangement... The second one was to lay the technology foundation. The third action relates to Moodle development. The fourth is communication with all stakeholders. The fifth is student intervention. And the sixth is data mining and modelling." (29133)
	Strategic position (of LA)	Not strategic	0	There is no conceptualisation vis-à-vis learning analytics and its broader strategic positioning. If there is learning activity in the organisation, this has emerged as a result of individual, agentic action by researchers or faculty staff, and not owing to organisational leadership.	Inductive	"We haven't done that yet, no. We haven't really done that. I'd probably characterise what we've got as sort of like a system in place that's sort of available. But whether or not it's rolled out as broadly as it could be, or whether or not it's systematically available, you know, we're using it in a systematic way, it's probably early days. So at the moment we've sort of got this ability, different people using it in different ways, and we haven't really got to a position of having a policy on it or a requirement to have it or any clear guidance, I suppose, on how it's used. Because not enough people are actually across what it's all about" (29136)
		Independent	1	Learning analytics is conceptualised as a complete and independent strategy, separate from, and in addition to, extant teaching, learning and business processes.		"We have a working group, um, and their role this year is to develop a strategy to go forward to academic board of the university. Um, and then a scoped project to go forward through the budget process next year. Um, so the focus of their activities this year um, are, first of all, suppose three major, they have three major sets of responsibilities. One is, ah, a very educational set of responsibilities which is to, to um, educate upwards. And outwards, about what learning analytics is, what it's not, um, what it can do and what it can't do. To establish for us what are the big questions that we want analytics to answer for us. Um, and then to propose a way forward.." (29135)

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		Embedded – strategic	2	Learning analytics is conceptualised as one in a range of strategies; it is not viewed as a solution but a tool to be used in conjunction with additional approaches. This positioning is a stated strategic objective. In this conceptualisation, LA might be embedded in another process, and not 'reified'.		"Ah, there are some working groups looking at this stuff but not specifically, like they're not working groups on Learning Analytics, they're more working groups for example, working groups around retention, attrition etc., that will of course interrogate the potential of analytics as a tool for that space. Um likewise um, you know we've got working groups around assessment, design etc., that will look at how Learning Analytics might be a useful part of that so it's not as if we're using Learning Analytics as the tool, it's more that we're totally aware of its potential in a number of domains... Indeed and part of that's because Learning Analytics is such a dare I say it, the catch all phrase for a whole bunch of data you can get. Um and you know there's different ways we can use the different data we get from different areas and we – I'm very much someone who I guess is driven more by useful engagements rather than a tool in itself… Yep so it's not about oh, what a fantastic suite of Learning Analytics tools we've got, this is brilliant, it's more okay, how do we get this greater good and if Learning Analytics can help us do it you know be it, then that's fantastic. And it'll be one of the tools in the tool box no doubt." (29139)
	Stakeholder Consultation	NA		There is no evidence of consultation with any stakeholders (senior management, faculty or students) before/during the development and implementation of learning analytics strategies.	[65]	
		Senior Management		Senior management are the only stakeholders consulted before/during the development and implementation of learning analytics strategy.		"Probably senior management group, probably about a year and a half, two years ago, um, when it was brought to our attention around the, um, early intervention type programs… What is the makeup of the main team driving LA? Well it's mainly um, IT, I mean at the moment within LTU it'd be the IT specialists and um, senior management. don't think faculty are that involved in it." (29481)
		Comprehensive		There is evidence of consultation, or planning for consultation, with senior management as well as additional stakeholders (i.e. faculty, students) before/during the development and implementation of learning analytics strategies.		"Really lifting the conversation up and saying it should be a very clear, large scale project, the direction of which is apparent to everybody in the University, that they feel like they've had an ability to contribute to that and they know what's coming so that we can make sure that the education for staff is appropriate, that we mitigate stress and that we also manage transitions in platforms in a way that means that people are not going to be impacted adversely during teaching… and they feel more confident and less stressed about how this piece is working for them and how that they can get on board and really enjoy the experience of using the technology. It's absolutely critical... We've started having that conversation with them saying what would you find useful. Because I think a lot of the time, the kinds of people that

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						typically make those decisions are designers and they might be high end IT users who can sometimes over complicate what the story is. My view is it's the average person on the street and it has to be presented in a very intuitive way for that person to understand. Look students use that all the time. They use Coursera all the time. I mean they use these platforms on a pretty daily basis. So they see this stuff and they come back and they say I like that, I like the simplicity of that, can we do something like that. So I have a stronger sense... It's much more mainstream for students to be doing MOOCs and giving me feedback and saying I use calm for this, I did this for this. They're self-starters, they actually get out there and find out what they can and do what they want to do. [Our] students are pretty out there, they are really very smart and they find opportunities and they take advantage of them and they're great advocates. They speak up really quickly and very intelligently about what they want… We've got a couple of committee's that provide advice around the day to day experience of the platforms, we also have our higher level group that look at the budget tracking on that group, we have a University IT committee that checks in on the progress of the road map and to date we've been under budget and on time so we're really trying to deliver a very professional, clear, transparent, robust process of improving enterprise platforms so any staff member in the University can find the information and feel happy… Yeah there's the University IT committee that's chaired by the Vice Chancellor and it ultimately checks on all of the IT projects. So they cascade up into that committee" (29485)
	Organisational Culture	Limited awareness	0	There is limited or no acknowledgment of the potential for organisational culture to influence the success of learning analytics.	[63, 66]	
		Recognised	1	There is strong acknowledgment of the potential impact of organisational culture on the implementation of learning analytics, yet little evidence of strategies to mediate the influence of these.		"And the other sort of resource is you know the harder bit which is the culture and to try and embed and think about how um our colleagues might engage with analytics as a tool. And that's a non-trivial challenge. You know we can build the world's greatest dashboard but if it's not a part of what our colleagues want to use then… At the moment you know for many of us we kind of engage with Learning Analytics. We've seen other people's dashboards, we know that exciting things that can happen but it's certainly not widespread um and that's one of the conversations we have to have you know, it's like you know well who, who takes responsibility for this? Do we push it down to level, is it program director level or is it you know something that happens at a broader institutional level, if it happens how do we flag things? What's the process by which we get colleagues to engage?" (29139)

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		Strategy	2	There is evidence of initiatives and approaches to strategically address cultural barriers to the implementation of learning analytics.		"Um, and the expectation is that they will, you know, they will do some thinking, they will do some talking, they've got a number of guest speakers already…We've had them come in, but they will also set up in second semester a series of public guest speakers. Um, reaching across the, again, just so that people understand what it might mean. I mean we already have a lot of literal kind of analytics projects and people are interested. But um, we've still got a high level of education that we need to do too among our staff, so that they do understand. And that they understand that implementing analytics is not a silver bullet." (29135)
	Building capacity	Limited awareness	0	There is minor or no mention of limitations of staff capacity for research, knowledge and understanding of learning analytics.	[67]	
		Recognised	1	There is an awareness of potential challenges that may arise due to staff capacity in using and interpreting data produced by learning analytics.		"We've actually got to better position ourselves to be able to actually respond and work with it. At the end of the day, working with the, the outcomes of data and analytics is really grass roots, coal face type work. So our issue is, how do we educate all of our academics and our support staff and so on as to what we want them to do?" (29136)
		Strategic approach	2	Specific strategies have been developed and implemented to reduce challenges that arise from the introduction of a new approach (e.g. numeracy/statistics programs).		"Another part of our analytic strategy is that we think there's no point in collecting a lot of data um, and bringing different data sets together and doing analysis if people don't understand enough about statistics to know what it means. So we have um, a whole project to improve the numeracy of our staff and students, so we developed a formal aware subject and we've been piloting it with academic staff; we've done that twice um, and we're not, it's now been approved to be offered as an elective to our students." (32256)
	Technology	N/A	0	There is insufficient discussion or low awareness of technological capacity and potential limitations of current technologies. Technology in this operationalisation refers to IT systems and software programs that will enable LA programs.	[46, 66]	
		Recognised	1	The limited capacity of technology in the implementation of learning analytics has been recognised but little action has been taken to mediate this. An Education Data Warehouse may have been established.		"So, um, what we really need… is performance information about how students are performing. And the biggest barrier we have there is just, I mean, it's pretty straightforward. The biggest barrier is just systems not talking to each other and having to put stuff into a data warehouse where you can get access to it." (29136)
		Strategic approach	2	Strategic efforts have been made to improve technology capacity beyond a data warehouse.		"But even at that scale we think we can't amass enough data to be able to tease out the behaviour patterns at the level of detail that we'd like to do it. So for the past, the, the, the, the way in which we approached it was to partner with ah, [partner name]… And our notion

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						there was that the, the, the private partner gathering tens of millions of dollars in investment would be, would have much greater leverage at developing that, that engine and that capability than we would. (29142)
	Funding	N/A	0	There is insufficient discussion of data to determine mediating effect of funding.		
		Constraint	1	Funding is identified as a limitation and/or hindrance to progression of learning analytics.		"We haven't got as much resourcing as we would like but I think everyone would say that." (29138)
		Affordance	2	Funding is perceived as conducive to growth and development of learning analytics.		"We have, like many universities, invested quite a lot in a systematic strategic data driven approach to a lot of things. This is only a, I mean, a whole sort of recurrent and capital budget process, has gone to a whole different model. Ah, our whole analytics profiles of courses and schools and faculties is way ahead of what it was five years ago." (29137)
Implementation	Ethics	Limited awareness	0	There is low to no awareness or mention of ethical implications of learning analytics.	[5, 33, 68]	
		Discussion	1	There is evidence of awareness and discussion of potential ethical implications that learning analytics may impose.		"Um, and then the other part of that is um, um, the policy work that will inevitably come out of it. And I've, I've held off for now on that, I mean I'm very aware of you know, a number of the ethical issues associated with use and misuse of data, the data privacy, with um, uh, the potential for acting on misinterpreted data, you know, all those kinds of issues, um, we've scheduled to start doing that policy work… So we would use our usual policy route, academic policy route, for this. The reason we're holding off is twofold. Uh, one to let people play first, and two to give these projects a chance to um, you know, produce some output that we could learn from." (32240)
		Policy	2	Changes have been applied to institutional policies in order to address ethical implications of learning analytics.		"The ethical use of the data is a separate advisory group to the governance group. There's good reasons why it was done like that… There's great potential for surveillance and uberveillance in this space, which is completely inappropriate… They would seek some advice and endorsement from the advisory committee. And that committee includes legal advisors, experts in surveillance, a couple of our associate deans education, our academic registrar, and myself… They've written guidelines for learning analytics… So last year, um, we conducted a survey of our students to determine what their expectations were from learning analytics, and to unpack what their concerns might be around privacy, surveillance and uberveillance that was possible through this. And that survey was completed by December last year and it's been used to inform the strategy." (29133)

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	Stage	Preparatory	0	There is evidence of implementation of systems and strategies in preparation for learning analytics activity (i.e. EDW, data collection, business analytics).		"So the first thing is looking at where a project where we're looking at the main enterprise teaching and learning systems, mainly the learning management system and lecture capture system, predominately. And looking at, um, how we can get data out of those systems that is useful for students and staff in informing their decision making. So we've got two people working in that area that are interfacing with real case requests from academics out in the community. And we're building up a series of use cases of analytics, so that's one sort of area, um, that is running alongside a more formal review of, you know, and it, it's an iterative, ongoing review, of what our internal analytics capacity is, and what other widgets or plugins or APIs are available in the market, and decision making process, we've got a sort of relatively formal decision making process as to whether or not we'd buy an off the shelf product or buy a piece of middleware or buy an API that will assist us." (29486)
		Early	1	There is evidence of data collection, interpretation and analysis informing 1-2 initiatives.		"We've got a project focusing on first year, um, retention and completion… And we, we used two types of data um, in our retention strategy… And those, those students are pr-, are identified and provided with um, particular support, targeted support that's um, intended to um, max-, optimise the chance that they'll remain in the university and, and, and complete the first year of their degree and progress into second year." (29134)
		Advanced	2	There is evidence of implementation of multiple interventions or initiatives informed by data.		"Having said all of that too, an example is there's a student success project, which has been quite successful around, you know, phoning up the students and, and helping them pass units and not drop out and all those sorts of things. You know, the things that are occurring in many unis… We've also been doing some work, um, really about, um, ah, I guess you'd call it the student journey, for want of a better term. We're starting to look at, we've done things about ah, looking at, we're trying to look at, work around the sequencing of units and the impact they may have. We're looking at, you know, the bottleneck units, where people sort of choke and die and it throws them off their degrees and we're trying to link that back to actual possible behavioural changes and how we let people mediate and get through that possible failure etcetera too. So then we might link back to actual genuine change in policy… We've been, we've done some prototyping around, um, you know, prerequisites and things. We've done heat maps that show, you know, if you studied these units you're more likely to pass these units… And you can see each little square on a page represents whether having studied that unit or you're passing. You can actually, in one spot, see, you know, the power of foundational units for some things. Where there might be sequencing issues that are going on and other, and you know, people fail if they haven't done a core prior unit or something like that… I guess we've been interested

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						a lot more about process, as opposed to the more traditional static sorts of data that exist too. So while we're interested in all the gender and those sorts of things that can be in your data and all the background ones, etcetera, we're more interested in the noise, the other things that are listening to the heartbeat of your institute. And so essentially things like, we've gotten in to the back of Blackboard and we've done a lot of work around patterns in how the students engage with that information, for example… You know, we've learnt a little bit about the presence of our students on campus and a range of things." (29489)
	Education Data Warehouse	N/A	0	There is insufficient discussion to determine scope of EDW, or no system is currently operational despite recognition of the need of an EDW for the implementation of LA.	Sophistication model [67]	"But the reality is, is that we're we looking at how we will build a learning warehouse let's say. We've collected these kinds of data and at this point it is still an abstraction although we are using our engagement with edX and… our installation of it to pilot the tools and the back end necessary they could serve as a model for it." (29138)
		Limited	1	An EDW has been implemented university wide, however data incorporated is limited to existing student information systems, including admissions and student record data. Engagement data is not included.		"Um, so [institutional EDW] is for all kinds of institutional reporting um, and this is really very specifically about learning and teaching… So the big, you know the big overall reporting, the progression, retention all of that sort of stuff, number of students in various categories and so on, has been rolled out. But what is good about that capability is that now we can go down to a inner study level and right down, you know it's not just, you know faculties. You can compare one faculty against another, you can look at success of students in, you know doing the same unit in one faculty and doing the same unit in another faculty." (29131)
		Comprehensive	2	There is evidence that learning/university engagement data (i.e. library use, orientation attendance, LMS engagement) is either included in the EDW, or a project is underway focused on embedding this data.		"We've spent a lot of time, money and effort putting in place a centralised data warehouse, which covers off all student information, staffing information, finance information, research information. And so we have a pretty comprehensive, very thorough map, or a very thorough warehouse of all of our data. And we're actually now using our various analytics tools which are available for us. Both from the perspective of just, you know, raw getting data and finding out how many students are doing what and why. But also using SPSS on top of that to drive decision making. So, [instituional initiative] is built on top of an SPSS module, which sits on our data warehouse. BlackBoard analytics is just a separate module over at BlackBoard… So what we'll be doing is looking at opportunities to interface the data that BlackBoard analytics is gathering back into the warehouse, in a sort of a more sort of pre-digested form. So that, essentially, we can just make, leverage it up centrally using the one system. Um, so we're pretty mature in terms of our data warehouse and our capability in data manipulation and analysis and so on." (29136)

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
	Scope	N/A	0	No scope has been identified for learning analytics, or there is no current implementation of learning analytic strategies.	Inductive	
		Retention	1	Learning analytic strategies being implemented are primarily focused on the retention of students.		"What we've tried to do over the last three years, few years is, is with some of our key um, goals around student retention and completion for example, which are really important goals for this university. I mean I know they're important for all universities, but, but I think we have a particularly challenging student cohort and so we've set, and we've had to advisedly set challenging goals for retention and completion." (29134)
		Learning	2	Learning analytic strategies being implemented are primarily focused on understanding and/or improving elements of learning.		"So we use learning analytics to optimise students' learning through the capture, analysis and reporting of data about the learners and their contexts. And then we have a particular focus on near real time provision of analytics to the students and the teachers when they're in their learning context. Whether it's face to face teaching or online teaching, or sort of blended… So, that goes back to what we defined learning analytics to be for, and it's optimised learning. So the data mining activities are in place to optimise the learning. All the corporate potential, commercial aspects of using this data set, there will be a [unclear 0:04:30.1] over that because that's not what learning analytics was installed for" (29133)
	Learning impact	Awareness	0	There is an awareness of the potential for learning analytics to influence learning, yet no operationalisation of how this might be achieved.	Inductive	"If we just look at the analytics rather than the bigger picture of all the data, I think, um... Well, the ambition, and, and it's, even it's closer than five years. Is that every academic will actually have a clearer understanding of how well the student in their class is actually coping… Um, and we really do have, or we really don't have clear indicators of how effective the things we're doing are with respect to actual learning. We can, we can somehow measure engagement. We don't know if we've actually delivered, you know, in terms of the student's learning outcomes." (29132)
		Action	1	There is evidence of operationalising data and/or implementing learning analytic findings to affect learning.		"Increasingly we are running analytics over the tops of um, our LMS for example, and getting um, course level engagement profiles of you know who, you know, which courses are making which use, uh, what use of which particular uh, tools collaborative participation tools or whatever it might be. And then feeding that back to staff and saying you know, here's a profile of the pattern of affordance of, of tool use in your degree program. And you can see that you know, there's a lot of collaboration going on in certain hot spots but the rest of the degree program's a bit light in this area. So just, you know, and then, and they're very crude forms of data, but it's an, the first modest attempt to put data in the hands of those closest to the ground." (32244)

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		Recursive	2	There is evidence that data is being fed back into teaching and learning processes and generating an effect.		“Then finally we, it alters our curriculum so now we’re realising things that are pretty obvious to the sector anyway, um, but I needed almost these data just to get faculties on board, so even though I was jumping up and down saying, “You need some very early low level assessments at the start of first semester, first year, so you can give good feedback quickly to the students.” So it, it’s helped, but none of the data show that, you see. So, so it’s helped us redesign our curriculum and our assessment processes which in turn will actually improve the retention and, and progress for the students so, and that will all have to be fed back into the model as well.” (29487)
	Vendor products	No Vendor	0	There is no plan to implement vendor product; learning analytics activities are entirely the result of in-house development.	Inductive	“Um, a third project that we’ve been engaged in is in um, we’ve developed and piloted a student dashboard. We were very buoyed by the reported successes in terms of the Signals project; we tried actually to buy Signals but we weren’t, just weren’t able to um, get good communication with the company that was selling it um, so we, we wrote our own.” (32256)
		Vendor lead	1	Evidence that vendor products have been implemented as major component of LA initiative(s).		“We’ve worked with [vendor], so um, we actually followed [another university’s] lead um, a year after they started working with [vendor] on their first year strategy. We’ve got a little unit that’s for putting our first year strategy and um, and, and we started working with [vendor]… We let them access our student data so they used, they were able to use that to help us um, ide-, you know, to set up, to choose the quantitative triggers, sorry, quantitative in-, indicators that we would use in our retention programme based on their experience with other universities, and um, and they did the data analysis in the first instance for us. But now we’ve got a really nice system set up so that um, because as we, and we use [vendor’s] call centre facility to assist us in our retention and success strategy.” (29134)
		Integrated	2	Vendor products have been implemented as part of LA initiative(s), in ‘partnership’ with in-house development.		“Um, we recognise that Learnline data is, is only one, uh, source of relevant data. Um, so we are looking at um, you know, how we might link this in with our data warehouse. You know, what the relationships might be between Learnline data and you know, library data, um, student info system data, um, you name it, there’s so many, you know, staff data. Um, so we, we, by no means take the view that learning analytics uh, is only limited to what the learning management system can tell us… We’re quite aggressively lobbying with uh, with Blackboard as their kind of, senior management, but also development levels, to integrate sets of data and to add little bits that aren’t there at the moment. Uh, and the two that most bring to mind, are the data sets involved with Collaborate, which has, um, become an incredibly important tool for us… So I, I wouldn’t say that we’re, I wouldn’t say that we’re just starting with our use of analytics and I wouldn’t say that

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
						we're only using external tools, I mean I think we've always worked with some form of analytics… Um, and it's just that in the, in the digital age, um, you know, the, the, the potential to do things faster and in an automated way are, are much more available than, than they were before. And, and so are we using external tools, yep, yep we are, but the data warehouse for example, it's not really a question of using the external tools, that's more a, you know, that's more wading into the data architecture ourselves." (32240)
	Evaluation process	Limited	0	There is limited discussion of evaluation, or acknowledgment of the importance of embedding an evaluation process within learning analytics, yet evaluation processes have not been fully implemented and embedded in processes. The institution may be committed to evaluation of teaching and learning, however learning analytics is viewed as the vehicle of evaluation, rather than an activity to be evaluated.	Inductive	"I think that there are some more intangible outcomes that would be harder to measure I suspect and, um, even just improve student engagement separate to, ah, retention is something I think we would want to try and measure, but I'm not entirely sure how we would do it... and I think that's part of our goal, too, the development of the DWBIs that it actually should, um, add value to the operations of the institution." (29140)
		Informal evaluation	1	There is evidence of analytics evaluation, but no evidence of a formal evaluation strategy.		"As an overall assessment of analytics at the institution, I don't know that I see one yet. Um, for individual projects, um, it's definitely there. Um, for my own, er, focus on sort of learning analytics, and particularly working with, er, the LMS, um, that's sort of my next step… I'd like to bring a little bit more of a robust data analysis on that, but the challenge with that is, I'm not sure all other institutions are working at this at the same pace as well, and so it's kind of hard to compare what we're all doing in, in, you know, relative to, to what we're doing." (29144)
		Recursive evaluation	2	There is evidence that information elicited through evaluation of a learning analytics process has been considered and will be integrated into future planning of learning analytics activities or strategies.		"We did do control groups… But in, in the short-term the, um, we did ah, take out a quarter of students, and based on their student ID, the last few digits of their student ID randomly um, didn't include them in some of the contacts… I think initially we, we were pretty keen to see if, what was working, what wasn't. So um, we did go down the path of doing a control, control group. And that does allow us to analyse the differences. And what we found was probably some of the early models and contact was having a bit more impact than the later ones… Early contacts seem to have a pretty positive impact, so the models we were running um, O Week, 1st Week, 2nd Week looked like they had a bit of a positive impact. It was pretty minor, to be honest, which was a bit disappointing, but um, but the ones closer to the census date may have had a bit of a negative impact… So, there might have been a short-term negative impact on, on the census date enrolments, um, but it's hard to tell whether it's a better student experience or not. So

Category	Dimension	Coding	Weight	Description	Theoretical/ Conceptual Foundation	Example
						they're, they're some of the things, though we haven't had a, I, I've been more, I'm interested in doing more analysis there." (29374)

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Appendix T: Evaluation Report

Evaluation Reflections

University of South Australia – SP13-3249

Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement

Background

The original aim of this project was to explore how learning analytics are being and are expected to be applied in the future at Australian institutions, with a focus on how and whether they are shaping teaching quality, student experience and student learning outcomes. Further, the project sought to situate these developments (current and planned) in an international context. Thus, in addition to reporting on Australian practices, the project will compare these with what is currently happening internationally in the institutional/ implementation space, as well as within the broader research agenda. It was hoped that the identification of good practices domestically and internationally would not only allow useful case studies to be developed that will be of interest to HE practitioners interested in pursuing an LA agenda, but importantly would provide insight into different strategies, approaches and processes underpinning successful LA interventions. Secondly, integrating the perspectives of leading researchers on LA in the project provided a means where current practice and thinking about future direction can be compared against the research potential of LA. Importantly, by bringing these data together, the project sought to develop a LA framework that will detail stages in LA implementation, and guidance on knowledge, skills, infrastructure, resourcing, capacity, training and other issues associated with a successful and sustainable program.

The guiding focus of the evaluation was to determine if the project's aims were achieved, and outcomes delivered, within budget and on time. As two strategic projects were commissioned in the area of Learning Analytics there was an agreed shift in the focus of this project in order to avoid duplication of efforts. One project, led by Charles Darwin University, focused on technology adoption and the application of learning analytics to address student retention. The second project led by the University of South Australia aimed to unpack how senior leaders conceptualise learning analytics and identify the key factors for successful institutional adoption. Hence, this team developed two separate yet complementary research studies. Study 1 sought to understand how senior institutional leaders perceived learning analytics including the drivers, affordances and constraints that shape LA within their institutional context. Study 2 engaged national and international experts in the field to identify the critical dimensions for implementing learning analytics.

Outcomes

The intended outcomes were to:

a) Identify the factors contributing or impending analytics adoption
b) Identify how Australian universities are planning and utilising analytics to support their learning and teaching goals, retention strategies, and the identification of at-risk students
c) Establish the underpinning elements necessary for long term and sustainable adoption of learning analytics

The major outcome was to be a report documenting current learning analytics practices and planned developments in Australia contrasted with international benchmarks. This would result in a maturity model that will allow institutions to evaluate their current practices and plans in the light of where they would like to go, and the next steps they should take. The original proposal noted the development of a Good Practice Guide consisting of illustrative case studies. However, following discussions with OLT this was revised to the development of a series of video case studies. These videos are in train and are to be integrated into the project website over the coming months. Again due to the duplication of projects in this space the second team has postponed dissemination strategies to avoid competition and replication.

Evidence

The first interactions between the Project and Evaluation Teams were at the OLT workshop for the 2013 Strategic Commissioned Projects, conducted in April 2014. Within the Learning Analytics Cluster, there were two projects, with this project being led by Professor Shane Dawson from the University of South Australia with partner institutions – University of Melbourne, University of Technology Sydney, University of the Sunshine Coast, Macquarie University and the University of New England. While several of the project team had collaborated in the past there were some team members relatively new to working together. There were also two dedicated project managers from UniSA – Ms Cassandra Colvin and Dr Tim Rogers.

In order to identify that the project's aims were achieved and outcomes delivered both formative and summative evaluation strategies were utilised. The Evaluation team was provided with access to the key documentation from the project team and were included in significant project team communications. In addition, a member of the evaluation team was a participant in virtual and face to face project team and reference group meetings.

Throughout the lifecycle of the project the evaluation team provided input and advice.

The Evaluator found several key factors that contributed to the successful achievement of the project aim and goals. These factors include:

- Regular meetings of the project team with the Evaluator from the beginning of the project, which were well supported by project plan updates and reports on activities.

This ensured that the team were provided formative feedback to further enhance the proposed project outcomes.

- Strong project management, as demonstrated by extensive and appropriate documentation and insightful input to the project from the project managers.
- Appropriate knowledge of institutional structures and priorities, ensuring that the activities undertaken related to institutional strategies and requirements in this emerging field.
- Diversity of skill set in the project team, which ensured a range of perspectives, breadth of analytical skills, and variation of insight into the project communication requirements.

The nature of the research methodology for the first phase - qualitative interviews – meant the bulk of this initial data gathering was undertaken by the two project managers – Cassandra Colvin and Tim Rogers to ensure a consistent interview protocol was followed. The team met at the University of Technology Sydney whereby all project partners contributed to the interpretation of the research analyses and potential impact for the Australian higher education sector. Following implementation of the recommendations from this meeting, project partner, Professor Karen Nelson undertook an audit of the research methodology with a strong focus on the coding protocols and aided the refined interpretation for the report. The team also presented findings and recommendations to Professor Shirley Alexander and Professor Buckingham Shum to ensure robustness, rigour of the methods and analyses as well as the feasibility and relevance of the findings for the sector.

Project Management

It has been documented that effective project management has the following elements:

- Identifying requirements,
- Establishing clear and achievable outcomes,
- Balancing the competing demands for quality, scope, time and cost,
- Managing the expectations of various stakeholders, and
- Adapting plans to overcome challenges.

From a Project Management perspective, the project was well managed and all stakeholder groups were involved. There was significant communication with all members of the project team and involvement of the reference group assisted with project execution and promulgation of project outputs.

From the outset it was evident that this was a well-led project with clear project goals and strategies. Inclusion of a member of the Evaluation Team in key project discussion provided formative evaluation and input throughout the project and was facilitated by the project leader in a positive and generative manner.

The leadership from Professor Shane Dawson along with the capable and conscientious oversight of Cassandra Colvin and Tim Rogers as Project Managers, were key factors in the success of this project.

Achievement of Outcomes

The key summative evaluation questions centred on whether the project was able to detail learning analytics implementations soundly grounded in the literature and data collected.

There were 32 interviews with senior Australian institutional leaders and 42 recognised international experts in the field of learning analytics agreed to participate. Of these 42 experts 30 began the brainstorming phase with 25 completing the entire sequence of concept mapping. The dissemination activities will take place over the next 6 to 10 months extending the lifecycle of this project.

Summary

The final report provides an excellent overview for anyone new to the field of learning analytics. It succinctly highlights the major domains and unpacks the major challenges to institutional implementation of sustainable learning analytics practices. The report clearly highlights the diversity of the nascent field of learning analytics and provides a model of the conditions necessary for sustainable uptake of learning analytics.

It is anticipated that this report will become a key source of information and guidance for any institution seeking to implement learning analytics.

References

1. Oblinger, D.G., *IT as a game changer.* EDUCAUSE Review, 2012. **47**: p. 11-24.
2. Siemens, G., *Keynote address: An introduction to the role of learning and knowledge analytics in education.* , in *Learning Analytics Knowledge* 2011: Lisbon, Portugal.
3. Ferguson, R., *Learning analytics: drivers, developments and challenges.* International Journal of Technology Enhanced Learning, 2012. **4**(5): p. 304-317.
4. Ferguson, R., et al., *Setting learning analytics in context: overcoming the barriers to large-scale adoption.* Journal of Learning Analytics, 2015. **1**(3): p. 120-144.
5. Greller, W. and H. Drachsler, *Translating Learning into Numbers: A Generic Framework for Learning Analytics.* Journal of Educational Technology & Society, 2012. **15**(3).
6. Macfadyen, L.P., et al., *Embracing big data in complex educational systems: The learning analytics imperative and the policy challenge.* Research & Practice in Assessment, 2014. **9**(2): p. 17-28.
7. Rogers, E.M., *Diffusion of Innovations*. 4 ed. 2010, NY, NY: Simon and Schuster.
8. Davis, F.D., *Perceived usefulness, perceived ease of use, and user acceptance of information technology.* MIS quarterly, 1989: p. 319-340.
9. Hall, G.E., *The Concerns-Based Adoption Model: A Developmental Conceptualization of the Adoption Process Within Educational Institutions*, in *Annual Meeting of the American Educational Research Association*. 1974: Chicago, Illinois.
10. Campbell, J.P., *Utilizing student data within the course management system to determine undergraduate student academic success: An exploratory study*. 2007: ProQuest.
11. Campbell, J.P., P.B. DeBlois, and D.G. Oblinger, *Academic analytics: A new tool for a new era.* Educause Review, 2007. **42**(4): p. 40.
12. Pardo, A. and C.D. Kloos, *Stepping out of the box: towards analytics outside the learning management system*, in *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*. 2011, ACM: Banff, Alberta, Canada. p. 163-167.
13. Siemens, G. and P. Long, *Penetrating the Fog: Analytics in Learning and Education.* EDUCAUSE Review, 2011. **46**(5): p. 30.
14. Macfadyen, L.P. and S. Dawson, *Mining LMS data to develop an "early warning system" for educators: A proof of concept.* Computers & Education, 2010. **54**(2): p. 588-599.
15. Wolff, A., et al. *Improving retention: predicting at-risk students by analysing clicking behaviour in a virtual learning environment*. in *Proceedings of the Third International Conference on Learning Analytics and Knowledge*. 2013. ACM.
16. Jayaprakash, S.M., et al., *Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative.* Journal of Learning Analytics, 2014. **1**(1): p. 6-47.

17. Pardo, A., et al., *Identifying learning strategies associated with active use of video annotation software*, in *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*. 2015, ACM: Poughkeepsie, New York. p. 255-259.

18. Dawson, S., *A study of the relationship between student communication interaction and sense of community.* The Internet and Higher Education, 2006. **9**(3): p. 153-162.

19. Buckingham Shum, S. and R. Deakin Crick, *Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics*, in *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*. 2012, ACM: Vancouver, British Columbia, Canada. p. 92-101.

20. Romero, C. and S. Ventura, *Data mining in education.* Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 2013. **3**(1): p. 12-27.

21. Baker, R. and G. Siemens, *Educational data mining and learning analytics.* Cambridge Handbook of the Learning Sciences:, 2014.

22. Baker, R.S. and K. Yacef, *The state of educational data mining in 2009: A review and future visions.* JEDM-Journal of Educational Data Mining, 2009. **1**(1): p. 3-17.

23. Knight, S. and K. Littleton, *Developing a multiple-document-processing performance assessment for epistemic literacy*, in *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*. 2015, ACM: Poughkeepsie, New York. p. 241-245.

24. Whitelock, D., et al., *OpenEssayist: a supply and demand learning analytics tool for drafting academic essays*, in *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*. 2015, ACM: Poughkeepsie, New York. p. 208-212.

25. Duval, E., *Attention please!: learning analytics for visualization and recommendation*, in *Proceedings of the 1st International Conference on Learning Analytics and Knowledge*. 2011, ACM: Banff, Alberta, Canada. p. 9-17.

26. Lockyer, L., E. Heathcote, and S. Dawson, *Informing Pedagogical Action: Aligning Learning Analytics With Learning Design.* American Behavioral Scientist, 2013.

27. Shute, V.J. and M. Ventura, *Stealth Assessment: Measuring and Supporting Learning in Video Games*. 2013, Cambridge, MA: MIT Press.

28. Lizzio, A. and K. Wilson, *Early intervention to support the academic recovery of first-year students at risk of non-continuation.* Innovations in Education and Teaching International, 2013. **50**(2): p. 109-120.

29. Nelson, K.J., M.E. Duncan, and J.A. Clarke, *Student success: The identification and support of first year university students at risk of attrition.* Studies in Learning, Evaluation, Innovation and Development, 2009. **6**(1): p. 1-15.

30. Nelson, K.J., et al., *Good practice for enhancing the engagement and success of commencing students.* Higher Education, 2012. **63**(1): p. 83-96.

31. Dietz-Uhler, B. and J.E. Hurn, *Using Learning Analytics to Predict (and Improve) Student Success: A Faculty Perspective.* Journal of interactive online learning, 2013. **12**(1): p. 17-26.

32. Kahu, E.R., *Framing student engagement in higher education.* Studies in Higher Education, 2013. **38**(5): p. 758-773.

33. Greller, W., M. Ebner, and M. Schön, *Learning Analytics: From Theory to Practice – Data Support for Learning and Teaching*, in *Computer Assisted Assessment. Research into E-Assessment*, M. Kalz and E. Ras, Editors. 2014, Springer International Publishing. p. 79-87.

34. Norris, D.M. and L.L. Baer, *Building organizational capacity for analytics.* EDUCAUSEreview Online, 2013: p. 1-58.

35. Davenport, T.H. and J.G. Harris, *Competing on analytics: the new science of winning*. 2007: Harvard Business Press.

36. Ferguson, R., et al. *Setting learning analytics in context: overcoming the barriers to large-scale adoption*. in *Proceedins of the Fourth International Conference on Learning Analytics And Knowledge*. 2014. ACM.

37. Bradley, E.H., L.A. Curry, and K.J. Devers, *Qualitative Data Analysis for Health Services Research: Developing Taxonomy, Themes, and Theory.* Health Services Research, 2007. **42**(4): p. 1758-1772.

38. Burla, L., *From Text to Codings Intercoder Reliability Assessment in Qualitative Content Analysis.* Nursing research (New York), 2008. **57**(2): p. 113-117.

39. Hsieh, H.-F. and S.E. Shannon, *Three Approaches to Qualitative Content Analysis.* Qualitative Health Research, 2005. **15**(9): p. 1277-1288.

40. West, D., et al., *Learning Analytics: Assisting Universities with Student Retention*. 2015, Office for Learning and Teaching: Sydney, Australia.

41. Novak, J.D. and D.B. Gowan, *Learning How to Learn*. 1984, Cambridge, UK: Cambridge University Press.

42. Dawson, S., et al. *Current state and future trends: a citation network analysis of the learning analytics field*. in *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge*. 2014. ACM.

43. Doherty, N.F., C. Ashurst, and J. Peppard, *Factors affecting the successful realisation of benefits from systems development projects: Findings from three case studies.* Journal of Information Technology, 2012. **27**(1): p. 1-16.

44. Klein, K.J. and A.P. Knight, *Innovation implementation overcoming the challenge.* Current Directions in Psychological Science, 2005. **14**(5): p. 243-246.

45. Jones, D. and D. Clark. *Breaking BAD to bridge the reality/rhetoric chasm*. in *31st Australasian Society for Computers in Learning in Tertiary Education Conference (ASCILITE 2014): Rhetoric and Reality: Critical Perspectives on Educational Technology* 2014. Dunedin, New Zealand.

46. Bichsel, J., *Research Computing: The Enabling Role of Information Technology*. 2012, Research Report, 2012 (Louisville, CO: EDUCAUSE Center for Applied Research, 2012), 28, available from http://www. educause. edu/ecar.

47. Manyika, J., et al., *Big Data: The Next Frontier for Innovation, Competition, and Productivity*. 2011, McKinsey Global Institute.

48. Uhl-Bien, M. and R. Marion, *Complexity leadership in bureaucratic forms of organizing: A meso model.* The Leadership Quarterly, 2009. **20**(4): p. 631-650.

49. Uhl-Bien, M., R. Marion, and B. McKelvey, *Complexity Leadership Theory: Shifting leadership from the industrial age to the knowledge era.* The Leadership Quarterly, 2007. **18**(4): p. 298-318.

50. Arnold, K.E., et al., *Building institutional capacities and competencies for systemic learning analytics initiatives*, in *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge*. 2014, ACM: Indianapolis, Indiana. p. 257-260.

51. Bourdieu, P. and L.J.D. Wacquant, *An invitation to reflexive sociology*. 1992: University of Chicago Press.

52. Gašević, D., S. Dawson, and G. Siemens, *Let's not forget: Learning analytics are about learning.* TechTrends, 2015. **59**(1): p. 64-71.

53. Drachsler, H. and W. Greller, *The pulse of learning analytics understandings and expectations from the stakeholders*, in *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*. 2012, ACM: Vancouver, British Columbia, Canada. p. 120-129.

54. Braun, V. and V. Clarke, *Using thematic analysis in psychology.* Qualitative research in psychology, 2006. **3**(2): p. 77-101.

55. Patton, M., *Qualitative Research and Evaluation Methods*. 3rd ed. 2002, Thousand Oaks, California: Sage Publications.

56. Seltzer-Kelly, D., S.J. Westwood, and D.M. Peña-Guzman, *A Methodological Self-Study of Quantitizing: Negotiating Meaning and Revealing Multiplicity.* Journal of Mixed Methods Research, 2012. **6**(4): p. 258-274.

57. Friesen, N., *Learning Analytics: Readiness and Rewards / L'analyse de l'apprentissage : état de préparation et récompenses*. 2013. Vol. 39. 2013.

58. Lodge, J. and M. Lewis, *Pigeon pecks and mouse clicks: Putting the learning back into learning analytics.* Future challenges, sustainable futures. Proceedings ascilite Wellington, 2012: p. 560-564.

59. Lodge, J.M. and A. Bonsanquet, *Evaluating quality learning in higher education: re-examining the evidence.* Quality in Higher Education, 2013. **20**(1): p. 3-23.

60. Ellis, C., *Broadening the scope and increasing the usefulness of learning analytics: The case for assessment analytics.* British Journal of Educational Technology, 2013. **44**(4): p. 662-664.

61. Baepler, P. and C.J. Murdoch, *Academic analytics and data mining in higher education.* 2010.

62. Goldstein, P.J. and R.N. Katz, *Academic analytics: The uses of management information and technology in higher education*. 2005, Washington DC: EDUCAUSE Centre for Applied Research.

63. Macfadyen, L. and S. Dawson, *Numbers Are Not Enough. Why e-Learning Analytics Failed to Inform an Institutional Strategic Plan.* Educational Technology & Society, 2012. **15**(3): p. 149-163.

64. Owston, R., *Blended learning policy and implementation: Introduction to the special issue.* The Internet and Higher Education, 2013. **18**(0): p. 1-3.

65. Arnold, K.E., S. Lonn, and M.D. Pistilli. *An exercise in institutional reflection: The learning analytics readiness instrument (LARI)*. in *Proceedins of the Fourth International Conference on Learning Analytics And Knowledge*. 2014. ACM.

66. Baer, L.L. and D.M. Norris, *Analytics Strategy, Capacity Building, and Transformation.* 2013.

67. Siemens, G., S. Dawson, and G. Lynch, *Improving the quality and productivity of the higher education sector: Policy and strategy for systems-level deployment of learning analytics*. 2013, Australian Government Office for Teaching and Learning: Sydney, Australia.

68. Heath, J., *Contemporary privacy theory contributions to learning analytics.* 2014.

69. Kane, M. and W.M. Trochim, *Concept Mapping for Planning and Evaluation.* . 2007, Thousand Oaks, CA: Sage.

70. Warren, K., *Strategic Management Dynamics.* 2008, Chichester, West Sussex: John Wiley & Sons: p. 626.

71. Sterman, J.D., *Business Dynamics: Systems Thinking and Modeling for a Complex World*. 2000, Irwin McGraw-Hill, Boston.