A three tier model to promote the institutional adoption of learning analytics

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Many institutions are making significant investments to build their learning analytics capability. However, creating a successful platform for large scale adoption of learning analytics (LA) is not simple. In this case study we describe the adoption of a three tier model designed for cross institutional engagement and implementation of LA at a medium sized tertiary education institution. We outline the actions taken at the three differentiated but interconnected levels of governance, projects and community. We analyse the results from activity in each of these three areas and, mark out a set of recommendations for future action that we anticipate will continue to drive and gain value from LA deployment across the institution.

Keywords: Learning Analytics, governance, principles, tools, community of interest.

Introduction

Despite the increasing investment across institutions in advancing their learning analytics (LA) capacity there remains a gap in documented large-scale implementations in higher education that detail successful strategies and activities (Ferguson *et al.* 2015). In this paper we describe a case study of an ongoing multi-level institutional approach to promoting the adoption of LA and developing organizational capability in this domain. This effort has been organized around three interrelated tiers of activity. In the study described here, the development of LA capability forms an important part of the institutional commitment to strategic goals, in particular those articulated within the learning and teaching strategy, digital transformation road map and, the deep commitment to student success and progress.

A multi-tiered approach was designed to ensure that learning analytics was brought into the organization in as an efficient and effective a manner as possible. One of the key aims was to avoid this enterprise falling into one of the two camps identified by Dawson *et al.* (2018), namely: (i) an instrumental approach to adoption led by top-down leadership, with large scale projects comprising high technology footprint with limited staff uptake or (ii) an emergent ground up activity with a strong consultation process but suffering major issues in scaling up and communicating its' value to all stakeholder groups.

Although the case study uses learning analytics as the key term for analytics activity, we were careful to acknowledge the differing domains of LA across the organisation. Indeed, one of the critical aims of this project was to align discourse and understandings around a complicated theoretical and technical domain that has recently emerged and is still evolving. Our starting point was to make a broad distinction between analytics that affect the wider functioning of the institution from those interventions that enhance the regulation of the teaching and learning environment and those methods and tools that are intended to help teachers (and potentially students) carry out their tasks more effectively (Griffiths, 2013).

Approach

An overview of the three tiers is shown in Table 1. The goal was to scope and define distinct layers of activity to help make the transition from existing discrete and dispersed pockets of activity towards aligned and embedded learning analytics deployment across the institution. Fundamentally, to support meaningful data driven interventions that would empower our teaching, academic, administrative and student stakeholders.

Table 1: Three tiers of cross institutional activity

	Level	Aims
Tier 1	Framework and Governance Model	To address the need for a strong governance model and develop a framework and principles to enable learning analytics to flourish.
Tier 2	Small Scale Projects	To support and manage pilot activity on the ground, building capability and testing proof of concept around LA tools and approaches and, explore the types of interventions that the institution could develop and support.
Tier 3	Community of Interest (see Fischer, 2001)	To build broad community engagement to sensitise and develop participatory understandings of learning analytics. To act as a sounding board for projects and policy development. To build capacity.

Method and Results

In this section we present an overview of the activity and progress achieved within each of the three tiers of activity described above.

Tier One: Learning Analytics Framework and Governance Model

It was apparent at the start of the project that deploying learning analytics tools and processes raises serious concerns around data governance, access to data and potential ethical (and moral) challenges to the way that a university operates and is made accountable (Corrin *et al.* 2019; Griffiths *et al*., 2016; Slade and Prinsloo 2013, Tsai and Gasevic, 2016). Here, we drew on previous European research on LA adoption in Higher Education which identified the need to develop:

> "a comprehensive policy that meets the requirements of learning analytics and considers multiple dimensions including an institution's context, stakeholders therein, pedagogical applications, institutional capacities, success evaluation, legal and ethical considerations, and a strategy that aligns with the institution's missions" Tsai and Gasevic (2016).

Within our context, where initially LA had a small profile across the institution, we decided to launch a policy initiative project. Our aim was to build a framework and a set of LA principles by working with key stakeholder groups, identifying relevant extant policy, associated relevant committee structures and use these data to help guide the building of an appropriate governance model.

Learning Analytics Policy Initiative (LAPI)

A key goal of this project was to develop a learning analytics framework, principles and guidelines for the implementation of LA across the university, in order to inform and enhance learning and teaching activities and outcomes based on using student data. To accomplish this, we adopted the SHEILA (Supporting Higher Education to Integrate Learning Analytics; Tsai and Gasevic, 2016) policy development framework that was adapted from the ROMA- Rapid Outcome Mapping Approach (Young *et al*., 2014). ROMA (see Figure 1) is an approach which is designed to develop effective strategies and evidence-based policy in complex environments.

Figure 1. Adapted version of the ROMA model used by the SHIELA project (Tsai *et al.,* 2018) and by Hainey *et al.* (2018).

This was conducted through a series of semi-structured interviews, focus groups and workshops with members of the University Senior Leadership Team (n=12), Faculty Deans and Associate Deans, academic and professional staff of the University Faculties and Central Service Units (n=39), and students (n=6). The data collected was analysed along the six dimensions, of: (1) mapping of (political) context; (2) identifying key stakeholders; (3) identifying desired behaviour changes; (4) developing an engagement strategy; (5) analysing internal capacity to effect change; and (6) establishing monitoring and learning frame-works (as demonstrated in Figure 1). All data was validated by the LA roundtable group (see details below).

There were three major outcomes from this piece of work:

First, by doing this ground work prior to adopting specific approaches to implementing LA, we were able to (1) be in a position to identify and implement solutions that would support our learning and teaching vision and values, and (2) bring academic and professional staff along, from the get-go, to the development of an environment where student, staff and organisational data are used in a thoughtful, deliberate, transparent and ethical way.

Second, we were able to develop a LA Principles and Framework that was validated through our community of interest (see Tier 3 activity described below). The purpose of this framework was clearly outlined in two key introductory statements within the document:

1. *Learning Analytics will support ongoing enhancement of learning and teaching practices and processes and should ultimately benefit all students*. The use of Learning Analytics has the potential to enhance student learning by enabling flexible, timely and targeted learning support interventions; contribute to better course and program design and planning; offer new ways of evaluating instructional materials and approaches; give student meaningful timely information about their own learning.
2. The purpose of this Learning Analytics Principles Framework is to ensure that all University Learning Analytics practices are carried out ethically, in a transparent way and in accordance with the University's core values of respect, fairness, empathy, integrity and responsibility.

The framework incorporated a number of the University of Edinburgh Learning Analytics Principles (2017) but contextualized to our specific New Zealand institutional and cultural context. These principles were gathered under the following headline sections:

1. The use of Learning Analytics will benefit the University culture of teaching and learning (with a special emphasis on Akoranga – collective responsibility for learning).
2. Student agency in Learning Analytics is acknowledged and supported.
3. Learning Analytics will be used in an ethical and transparent way.
4. Learning Analytics will be practiced responsibly, in line with the principle of Kaitiakitanga (Protection)
5. Good Governance (Kāwanatanga) will be core to our approach to Learning Analytics.

Third, it provided an evidenced and consultative platform from which to build a proto-governance model that could be worked through with senior leadership at the university (Figure 2). To support this governance model we mapped the key strategic drivers for LA adoption to the desired operating model (Table 2).

Table 2: Mapping strategic drivers to governance and the desired features of the target operating model

Strategic drivers	Governance	Operating Model – addresses:
• Student Success • Revenue • Learning and Teaching • Capability Development	• Bring analytics safely to scale • Ensure adoption of whole of student journey approach (focus on retention and completion) • Apply Learning Analytics Principles • Enable the development of a data ethics, policy and framework • Enable key learning analytics project to deliver on outcomes	• Data access • Interfaces • Agency & authority • Roles and responsibilities • Transparency & explainability (e.g. of any algorithms deployed) • Assurance - operationalization of data ethics principles • Indicators and metrics

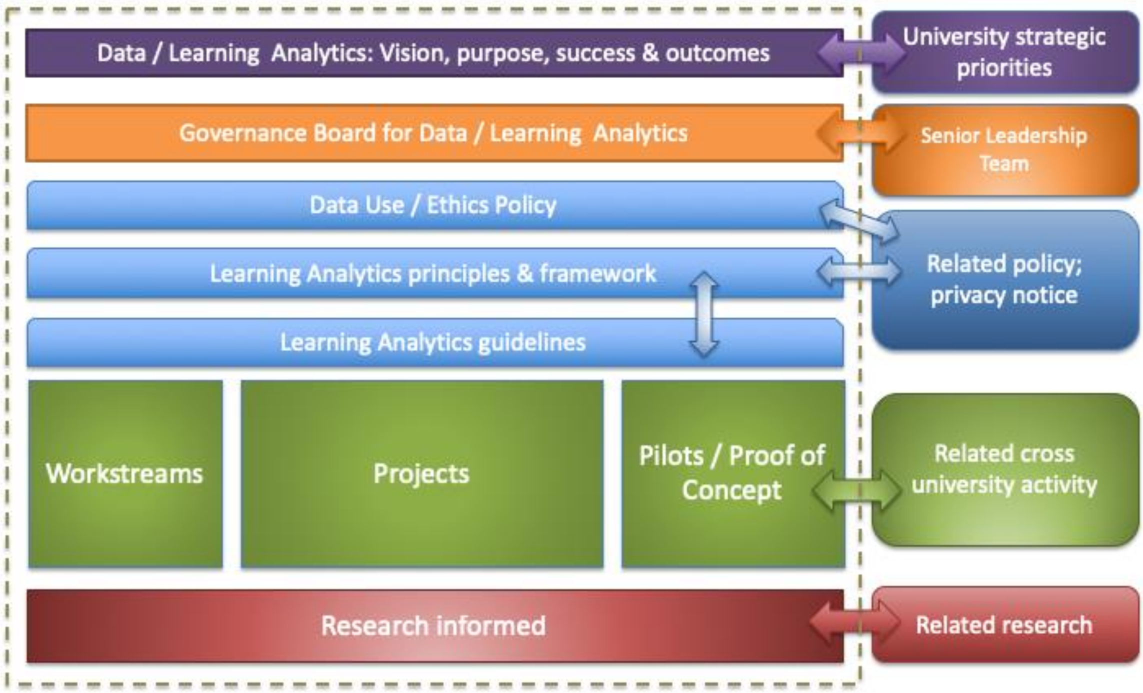

Figure 2: Proto-governance model for LA anchored to intuitional processes, policy and leadership. The model delineates activity associated with data and learning analytics (within dotted line) and maps each layer to the wider institutional strategic drivers, governance and related cross institution activity.

Finally, the adapted ROMA approach provided a mechanism by which to sensitise various parts of the institution to the potential for small scale pilot activity as described below. This process was particularly important in uncovering the internal capacity for change (ROMA Item 5) and linking the desired behaviour changes we might want to see (ROMA Item 3) to the engagement strategy (ROMA Item 6).

Tier Two: Small scale pilots

For this tier of activity, the scope was confined to tools and approaches that utilize learning data to support, understand and optimise learning. The key stakeholders in these five pilots were academics and students. We explored the following areas in a rapid, agile manner to determine their potential for future, larger scale project initiation (Table 3).

Table 3: Five small scale pilots to test LA approaches and tools

	Tool	Description
1	Learning Management System (LMS) and Lecture Capture embedded tools	- the set of dashboards and data visualizations of student activity and performance that can be used to inform teaching staff about student learning and course content design.
2	StudentVis	- a tool developed by the School of Engineering and Computer Science that provides a range of visualizations on student assessment progress through courses, used to support identification of students at risk of non-completion or areas of course assessment design that may require modification.
3	OnTask	- a tool for providing mass personalized feedback to sub-populations of students based on performance and activity conditions within a course (see https://www.ontasklearning.org/).
4	AcaWriter	- a formative feedback tool that uses Natural Language Processing (NLP) to provide automated feedback to students on academic writing (see https://acawriter.uts.edu.au/).
5	Quantext	- a text analysis tool for quickly extracting insights from written texts including short answer test questions, teaching evaluations and textual feedback data (see https://quantext.org/index).

This was an exploratory activity with a small number of engaged academics, students and support staff being selected for each pilot area to critically engage with the tools over a short two months timeframe. Participants were asked to reflect on their perception of value of the tools, what limitations or challenges they presented and what desires they had for improvements or changes to the tools that would better serve their needs. In addition, they were asked to reflect on requirements for operationalizing the tools, or similar type of tools, within their faculties. The general pilot approach involved a brief introduction to participants on the respective tools, an offer of support for using the tools during the pilots, as needed, and a subsequent process for gathering feedback - either through interviews or written feedback to scripted questions.

From the data gathered we were able to make judgements about both the perceived value of LA tools and approaches that were worth pursuing as full pilots:

Application-specific findings

- Though the LMS is a primary source of data on student activity for most faculties, it is apparent that the embedded analytics tools are too complex and don't meet the needs of lecturers to monitor students' progress. The Performance Dashboard was the most favoured tool because it quickly provides data on students with a single click but the range of data points displayed are too limited and the dashboard unable to be customized to meet specific needs . Participants were generally satisfied with Lecture Capture video viewing activity dashboard but indicated that monitoring viewing activity was less priority than other areas.
- The StudentVis application and corresponding support model provides the university with history of practice that can be drawn on to support efforts around monitoring and responding to student progress.
- OnTask: Generally, participants were enthusiastic about the tool, recognizing its power to administer personalised feedback within large courses to specific subsets of students based on assessment and activity conditions. The granular control and customization of OnTask was recognized as particularly suited to supporting lecturers and course staff in their teaching feedback tasks. The learning curve to use the tool is significant and requires fairly technical instructors and / or adequate support both for sourcing and importing data into the tool, setting up the conditional rules and understanding the when and how of effective feedback.
- AcaWriter: Participants were enthusiastic about the tool, while recognizing the demonstration version had limitations. Students noted the value of the tool to support student agency and timely feedback. Participants see the tool supporting a number of use cases including: for prospective students thinking of undertaking academic study, students early in academic study, mature students unused to academic writing, non-native language learners as well as higher level learners submitting journal abstracts. In addition, the tool can help academics and tutors grade fairly and avoid biases. Concerns were raised, however, around the potential of the tool to persuade students toward formulaic writing. The language used in the analysis report and feedback needs additional explanation, or changed to fit the local institutional context. Additional genres of writing, additional feedback and resource examples are also desired. Some interface issues were also identified.

- Quantext: Participants were generally positive about the tool and thought that it had the potential to offer new insights into how students learn in the course, their levels of understanding of subject-specific concepts and terms. They also thought that the tool could provide useful feedback on the quality of assessment (questions and instructions) and teaching materials, and could help them improve the contents of lectures and tutorial. The main limitation that participants commented on was the time-consuming nature of the data analysis and its interpretation. They felt that one-on-one support would be needed, especially in the early adoption stages, in order to understand the available options and functionalities. They thought that the most effective way of using the tool would be in conjunction with an academic developer, who could help them with the interpretation of the results and suggestions on how to improve the course and teaching.

General LA pilots' findings and conclusions

- For LA practices to be successful, capability development as well as technology implementation need to be addressed. Though participants in the pilots were largely hand-picked from engaged academics and students, many complained of lacking the time or capacity to learn how to use the tools, interpret and act on them effectively. This is true not only of lecturers but also students who need support to learn how to use LA tools effectively to support their learning.
- Academics desire a just-in-time, one-to-one support model that can help them explore options for meeting their analytics needs as well as provide how-to support.
- Overall, there is a need to coordinate efforts in the LA space across different university strategic drivers and service areas. We noted overlaps between StudentVis, CRM Advice (another system being piloted within student academic services) and OnTask. While the drivers and scope may be different, participants in the LA pilots saw these tools serving a similar need and are seeking holistic approaches to monitoring student progress and support.
- Effective LA tools are characterised as easy to use, fast, customisable, accurate, intuitive and, preferably, aggregated in a single location.

Tier Three: Open community building and shared research enterprise

In parallel with the LAPI project described above we instantiated an open forum for sharing LA practice with the aim of building consensus around the terminology, discourse and sites of activity across the institution. This community of interest was developed through a regular (quarterly) series of hosted roundtable meetings. These followed a distinctive pattern of invited speaker, sharing of new and ongoing work, ending with an open forum discussion on broader analytics themes. In order to establish grounds for future cross-university LA cooperation, having an iterative and open conversation was critical. This is because personal interactions help to establish anthologies of meaning for a common cooperative language and to find common gaols (Weiseith *et al*., 2006). Conceptualising this cooperation as social practice, we aimed to promote institutional learning (Creamer & Lattuca, 2005). Participant numbers averaged around thirty with a wider mailing list of over 100 interested individuals across the organization. The LA principles were validated through repeated exposure to this group, over a period of 12 months. The attendees acted as a catalyst for discussions within their own faculty and CSUs and became the LA champions for change. Membership of SOLAR (Society for Learning Analytics Research) was seen as an important enabler, providing staff an avenue to access capability development opportunities. Through this work we were able to map the analytics related activity across the organization at a very early stage (Figure 3).

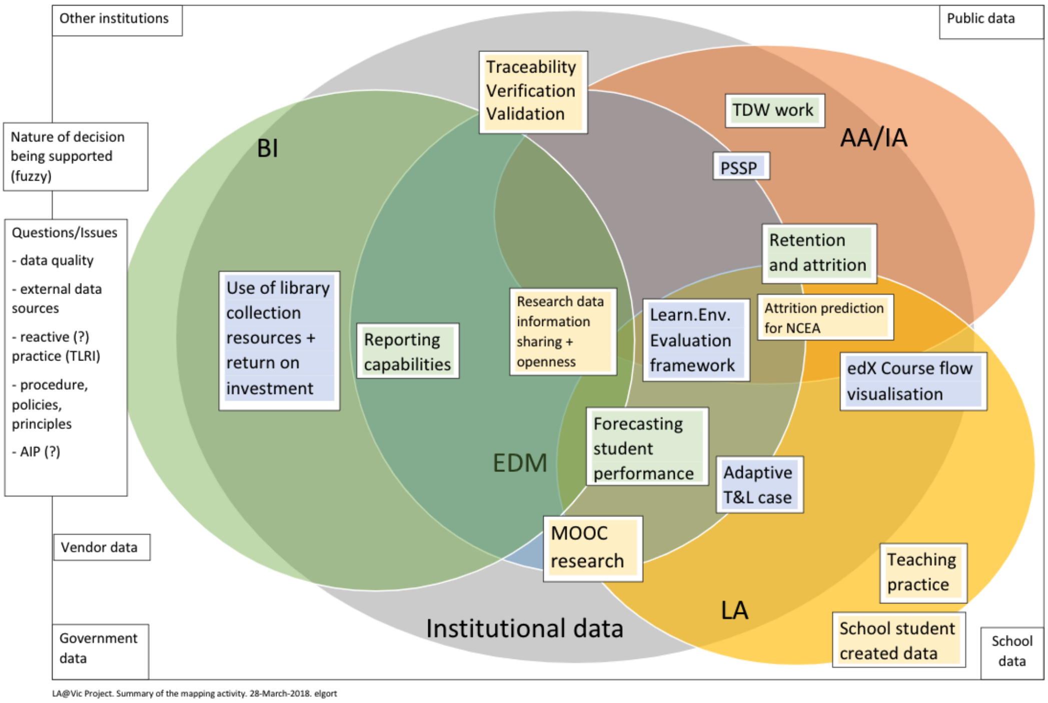

Figure 3: Mapping LA domains across the institution (BI – Business Intelligence; EDM – Educational Data Mining; AA/IA – Academic/Institutional Analytics; LA- Learning Analytics)

Discussion

The work here speaks to the five critical areas identified in Colvin *et al.* (2017) for developing maturity in LA that cover: technological readiness; leadership; organisational culture; staff and institutional capacity; strategy. The eventual benefits of adopting a multi-tiered approach have far outweighed the initial challenges experienced in pulling together disparate and sometimes competing academic and business areas of the institution. Patient and sustained engagement across all of the levels of the organisation have promoted deeper understanding of the value of LA and the identification of clear areas of organisational activity (Table 4). It has allowed a steady alignment to institutional level strategic goals via the instantiation of a consultative governance board to enable and steer the benefits of managed data use towards institutional outcomes understood by senior leaders.

The three tier approach described in this case study eschews the linear maturity model such as that described by Siemans, Dawson and Lynch (2013) in their Learning Analytics Sophistication model where capability and systems are integrated on a maturity continuum. It resonates more with process style models that operate at a programme level (Ferguson *et al.*, 2015). The important added dimension that the three tier design acknowledges is that LA implementation should be iterative, dynamic and sustainable. Here we note Colvin *et al.*'s (2015) model of Strategic Capability whereby the actual performance of LA implementation helps generate future capacity in the ability to conduct LA. As observed by Colvin *et al.,* (2015) and apparent in the approach accentuated in the model described here, the use of user-centred, rapid, prototyping and iterative activities (Gulliksen, 2003) has been a pivotal mechanism for gaining traction and stakeholder buy-in.

As described elsewhere in the literature, the establishment of a clear vision and purpose for learning analytics is vital and can be successfully achieved through the development of policy and procedure (Colvin *et al.* 2017). The instantiation of a governance board with clear line of sight to senior leadership has been a critical step and, was a direct response to avoid the documented failures that can occur in LA projects if this layer is not put in place (Macfadyn and Dawson, 2012).

In terms of taking learning analytics and principles through to policy development, this is a complicated area. Like many institutions, our own policy setting processes and procedures require visibility across multiple institutional touchpoints and navigation through several committee layers. One of the challenges has been to untangle this route and find agreement across many interested parties while championing transparency of major concerns such as privacy, security, data ownership and control.

Institutionally sited research (Elgort *et al*., 2018; Lundqvist *et al.,* 2018) has remained an important component in supporting LA activity, though we have acknowledged the tension that the rapid but often independent progress in the LA research domain can create in the gaps between findings and their translation into practice (Dawson *et al.,* 2015). Overall, we have uncovered a strong desire for effective LA tools that can enhance teaching and learning practices and student support, as well as a growing interest in how these tools can link learning design with LA (Corrin *et al*., 2018). The importance of community building cannot be underestimated, and functioned as a driver to sharing knowledge and consensus building. This was critical in helping cross pollinate institutional activity and, for example, raising the level of conversation to key drivers such as the importance of linking pedagogy to analytics.

Table 4: Institutional analytics organised across four pillars of activity

Pillar 1 - Student focused institutional analytics:	Pillar 2 - Learning Analytics:	Pillar 3 - Data Analytics:	Pillar 4 – Research:
- Macro/meso level; - Retention metrics; - Defined success via KPIs; - Completion of courses across the university as a whole; - Audience/s: -Support services -Student - Governmental level reporting; - Crosses prospects and current students.	- Micro level (e.g. specific courses and degree programmes); - Focus on the learning and teaching practices; - Audience/s: - Staff (lecturers, tutors, course administrators) - Students - Maturity in LA principles and framework is an important enabler; - Staff capability and engagement are critical success factors.	- Macro level; - Educational data mining; - Predictive modelling; - Academic Analytics; - Maturity in data governance is an important enabler.	- Individual/Group; - Actively encouraged and supported; - Human Ethics Committee line of sight; - Driven institutionally by research strategy and associated priorities; - May inform central university data analytics programmes.

Conclusions

The value of a multi-tiered approach has been in helping address the complexities of cultural change, organisational capability building and advancing our technology maturity. Our current situation is one of increased awareness in the potential for learning analytics across the whole institution. As we transition from a data siloed to a data informed organization these tools, activities, process and conceptualizations are becoming increasingly aligned and supported.

Four areas critical for success have been identified going forward:

- Tools: Undertake further appropriately resourced additional pilots of LA tools to gather sufficient data to verify conclusions and establish requirements for operationalizing solutions across the institution.
- Data: The criteria for the selection of future enterprise software solutions should include the availability and potential to support learning analytics. Where limitations are identified within core platforms, alternative tool solutions should be sought to fill the gaps such as third-party integrations or data platform solutions that can harvest the data and provide meaningful dashboards and visualizations.
- Support: Establish and embed a model for supporting LA that includes: functional and pedagogical support for lecturers and students using campus-wide deployed LA tools; just-in-time support for lecturers requiring help with *ad hoc* LA-related questions and exploration tasks; and continuous capability development activities.
- Governance: Ensure a coordinated approach to analytics tools investigation and implementation across academic, service and reporting areas to ensure an integrated, connected approach to addressing LA outcomes.

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