Tailoring Learning Analytics for Success: Insights from a Comparative Study of Australian Universities

Jo-Anne Clark, David Tuffley
Griffith University

Learning Analytics systems are emerging as a powerful tool for student success, optimising curricula, and informing data-driven decisions. However, these will not be achieved without effective implementation strategies tailored to institutional contexts. This study compares the learning analytics practices of five diverse Australian universities, offering a nuanced exploration of the similarities, differences, and patterns that characterise their adoption journeys. We will work to identify the factors that contribute to successful implementation and enhanced impact. Our findings emphasise the importance of aligning learning analytics initiatives with institutional contexts, student demographics, and unique needs, emphasising the necessity of tailored approaches that resonate with stakeholders and address specific challenges. Our intention is to provide a practical roadmap for Higher Education Institutions seeking to benefit from learning analytics, giving them the means to harness the full potential of these tools.

Keywords: Learning analytics, Information systems success, Learning and teaching, Higher Education Institutions, Qualitative evaluation.

Introduction

Higher Education Institutions (HEIs) have been using Learning Analytics (LA) tools to gain insights into elements of learning and teaching through the analysis of student data generated from various systems. LA has the potential to transform the way HEIs support student learning and improve teaching practices (Tzimas & Demtriadis, 2024). LA can help identify underperforming students for early intervention, enabling them to change their behavior and potentially improve student success and retention (Arnold & Pistilli, 2012). LA data offers opportunities to support contemporary learning and teaching practices by providing insights for learning design and pedagogy (Kovanovic et al. 2021; Ifenthaler & Gibson, 2020; Tsai et al. 2020). Students' digital traces can be analysed to establish patterns influencing their learning behavior (Reyes, 2015). One of LA's main uses has been to track and predict learners' performance, identify potential issues, and detect at-risk students for targeted interventions to improve achievement and retention (Johnson et al. 2011; Wong et al. 2017). LA enables educators to base decisions about student learning on evidence and better understand engagement levels, facilitating ongoing feedback between educators and students, potentially improving the learning experience (Avella et al. 2016; Wong et al. 2020). Current studies have shown how LA tools can assist with a range of activities at HEIs to enhance students' learning experiences (Rates & Gašević, 2022). Our findings can inform strategic decision-making, facilitate knowledge sharing of best practices, and guide the development of LA capabilities that are tailored to diverse institutional contexts and needs.

HEIs have been using learning analytic tools to collect information about students and how those students navigate their way through university (Rubel & Jones, 2016). According to Wang et al. (2017) educators can gain insights into elements of learning and teaching through the analysis of student data. HEIs can use the vast amounts of data generated as students use the LMS (e.g., Blackboard Learn) and in systems like Curriculum Management Systems (CMS) and Learning Curriculum Management Systems (LCMS) (Sharma et al. 2011), to meet goals of improving student success and increasing retention. LA can help identify underperforming students and intervene early enough to allow them the opportunity to change their behaviour (Arnold & Pistilli, 2012). The potential for LA to predict and improve student success and retention warrants closer investigation. LA data can offer opportunities to support contemporary learning and teaching practices

(Kovanovic et al. 2021; Ifenthaler & Gibson, 2020). LA has the potential to enhance education by providing insights for learning design and pedagogy that would otherwise not be available today given the accessibility and data and advances in technology (Tsai et al. 2020). Students when using systems leave digital traces that can be analysed, and patterns can be established that can influence a student's learning behaviour (Reyes, 2015). One of the main uses of LA has been to track and predict learners' performance as well as identifying potential problematic issues and students at-risk (Johnson et al. 2011). Educators can also identify at-risk students and provide an intervention to enable students to have better achievement and therefore retention (Wong et al. 2017). Educators are now able to base their decisions about student learning on evidence and this has become increasingly important to better understand student engagement levels (Wong et al. 2017). It can also facilitate ongoing feedback between educators and students which has the potential to improve the learning experience for students (Avella et al. 2016; Wong et al. 2017). Current studies have shown how LA tools can assist with a range of activities at HEIs to enhance a student's learning experience (Rates & Gašević, 2022). Although, Tzimas & Demtriadis (2024) claim that LA has still not met student's needs.

Data-driven decision-making can involve making use of data, such as that found in LMS, CMS and LCMS (Sharma et al. 2011) to inform the educator's judgment rather than rely on intuition and institutional culture, as done previously (Dietz-Uhler & Hurn, 2013; Long & Siemens, 2011; Olmos & Corrin, 2012; Slade & Prinsloo, 2013). LA can be used to record and analyse the frequency with which students log in to their LMS, including engaging with the course material, which can predict how they would perform in their course or program (Smith et al. 2012). These patterns of engagement may be reliable indicators of the quality of the students' learning experience.

The collection of data at HEIs is widespread, and concerns have been raised as to whether the data collecting activities are beneficial to student's learning (Arnold & Sclater, 2017). This paper shows the application of the DeLone & McLean (2003) model of information systems success to five large, multi-campus, Australian universities. The study focusses on the LA systems at each university and how these systems can potentially improve learning and teaching and likely student outcomes.

Learning Analytics

The literature published on the use of LA to gain insights into learning and teaching is substantial (Greller & Drachsler, 2012). LA researchers have examined the prediction of student success (Jovanovic et al. 2021), uncovered improvements to learning strategies including assessment and feedback, looked at social networks in learning, how LA enhances student retention, how it improves the quality of feedback, and how it informs teaching practice. The literature has also examined LA adoption, deployment and implementation strategies and examined the principles for ethics and privacy protection of student data and developing policy around LA systems use (Gašević et al. 2022; Rubel & Jones, 2016; Kitto and Knight, 2019). It is still unclear how HEIs are to incorporate the ideals of respect, privacy and openness and informed consent into technical and pedagogical processes or how to translate data protection responsibilities into analytical practice (Wintrup, 2017). While these studies have furthered the field of LA research, they most often looked at one-off applications of LA or ad hoc systems (Nguyen et al. 2021). Dollinger et al. (2019) believe there is a gulf between researchers and users which in turn can reflect on the differences between the design of LA systems and their use. The authors suggest a more Human-Centred Design and participatory approach needs to be taken. The approach needs to consider elements such as the specifics of a school within HEIs, the context of how the teacher and student understands LA, the accessibility of platforms, and the elements of research design (Dollinger et al. 2019).

Information Systems Success

The body of work encompassing the information systems field is substantial. Researchers have been evaluating information systems using models and theories for more than three decades, seeking to understand successful information systems and information technology implementations in organisations (Gable et al. 2008; Davis, 1996; DeLone & McLean, 1992). An information system is that which involves the gathering, processing, distributing, and the using of information by input, processing, and output, with a storage and feedback component (Beynon-Davies, 2013). The authors view LA systems as information systems, thus LAIS (Learning Analytics Information Systems) as they process, collect, evaluate, analyse, and report organisational data for the purpose of decision making (Campbell et al. 2007). The updated DeLone & McLean model (2003) which has been cited in thousands of papers and is considered one of the most influential theories in information systems research is used in this study (Nguyen et al. 2015). The model provides a solid basis for examining the success of LA implementations, particularly in assessing whether LA can improve student outcomes.

Information systems success is categorised in the DeLone & McLean (2003) model using three classifications (Figure 1).

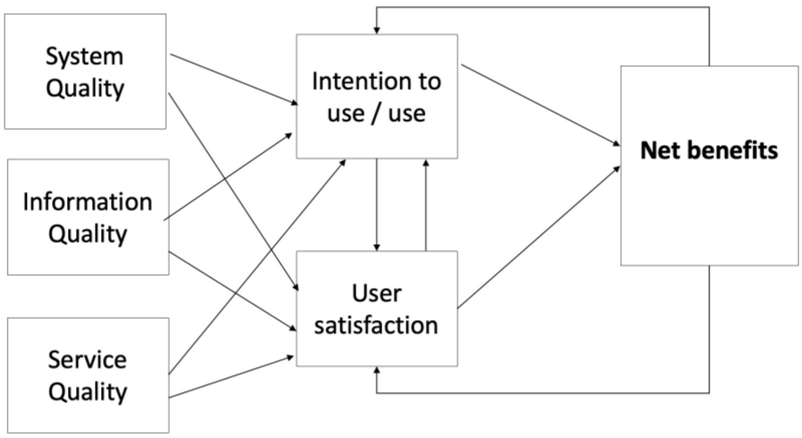

Figure 1: The updated DeLone-McLean information system success model (DeLone & McLean, 2003).

Firstly, the model examines the Information Communication Technology (ICT) system or functionality of the system. Secondly, the model focuses on the usability of the system and how users interact with the system and whether the system interface is user friendly and evaluating whether the system achieves its intended goal. Finally, the model focusses on the overall net benefits of the system, including how the information system's overall impact is felt as both an individual and from an organisational perspective (Nguyen et al. 2015; Beynon-Davies, 2013).

Research Approach

This research employs a case study methodology across five demographically diverse Australian universities. Case studies can produce insights that are unattainable through other methods (Rowley, 2002). Cross-referencing multiple cases further enhances the validity and generalisability of observations (Rowley, 2002; Yin, 2013). This approach is also useful for conducting exploratory research when there is little prior understanding of a phenomenon (Järvinen, 2001), allowing examination of real-world contexts and cultural dimensions (Yin, 2011).

An interpretivist approach was adopted, viewing reality as socially constructed and understood through individuals' interactions with larger social systems (Cantrell, 2001). Template analysis, a form of thematic analysis balancing flexibility and structure (King & Brooks, 2017), was used for qualitative data analysis. Initial a priori codes were derived from the DeLone & McLean (2003) model, based on theoretical readings. The data was then analysed and organised into a scheme using these codes (Blair, 2015; Schwandt, 2014).

The interview protocol of 32 questions was developed from related qualitative investigations (Ojo, 2017; Hopsapple & Lee, 2006; Wang et al. 2007) and categorised according to the DeLone & McLean model (2003) constructs, such as user satisfaction, net benefits, intention to use, systems quality, information quality, and service quality. Questions concerning the system's impact on teaching and learning were incorporated, aligning with the updated DeLone & McLean model (2003).

University case studies

Five Australian HEIs, consisting of three metropolitan and two regional/combined regional-metropolitan universities with diverse demographics, consented to participate as case studies through a random sampling technique (Seawright & Gerring, 2008). This diverse data source provides an inclusive picture of LA implementations across Australian universities.

- University One, located in an agricultural region, specialises in online programs, and has established a reputation for quality despite its remote location, with a significant online student enrollment.
- University Two caters to a diverse student population, including mature-age, first-in-family, low socioeconomic status groups, and professionals seeking career advancement through higher education.
- University Three, a regional multi-state institution, is an acknowledged leader in online service delivery, serving students from various regional Australian backgrounds, such as low socioeconomic status, first-generation families, mature-age individuals, and professionals.
- University Four is a public research-intensive metropolitan institution catering to a middle-class to upper-class student body and attracting high-entry-score students due to its elite status nationally and globally.
- University Five is a public, research-focused metropolitan institution with one campus located in a central business district (Clark & Tuffley, 2023).

Research Results

The DeLone & McLean (2003) model-based interview questions were used to investigate the effectiveness of LA system implementations. Three to five participants were selected at random from each university after the universities agreed to participate. There were twenty-three participants in the study overall. Every university had a different recruitment procedure. While key employees at some universities recruited the volunteers, others had strict ethical procedures that they had to adhere to. Managerial positions, instructional staff, LA support personnel, user designers, and data scientists were among the participants' roles. The first question posed to the responses concerned the kinds of LA systems that each university had put in place. All facets of the DeLone & McLean (2003) model, such as system quality, information quality, service quality, intention to use, and user happiness, were also questioned.

Nearing the completion of the interview, participants were asked to identify, under the net benefits category, (a) any advantages they thought the learning and teaching systems had for their decision-making, and (b) how learning and teaching were benefited overall by LA (DeLone & McLean, 2003). Two new themes emerged from the data analysis, but the analysis started with priori themes based on the DeLone & McLean model (Figure 2).

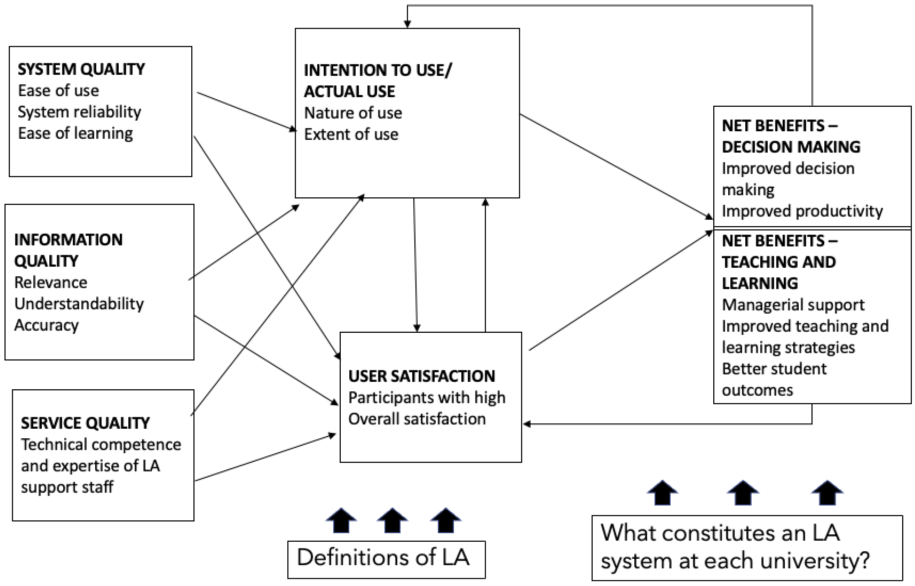

Figure 2: Summary of DeLone & McLean themes

As Australian universities continue to implement LA systems aimed at enhancing student outcomes and optimising curricula, it will be helpful for those universities embarking on this journey to have a comprehensive understanding of critical success factors.

In this study we have employed a comparative analysis approach across five case studies to find similarities, differences, and observed patterns influencing the adoption and impact of LA initiatives.

By examining convergent factors around system usability, information quality, and institutional objectives, as well as divergent factors in the form of technical implementations, organisational approaches, and maturity levels, valuable insights might be derived. This multi-site comparative analysis examines key drivers such as user-friendliness, data literacy, governance frameworks, and contextual tailoring.

These findings can inform strategic decision-making, facilitate knowledge sharing of best practices, and guide the development of LA capabilities that are tailored to diverse institutional contexts and needs.

Convergent factors

All five universities had implemented some form of a LA system set to collect and analyse student data, reflecting the widespread recognition of the potential value of LA in higher education. This proliferation underscores the need for systematic evaluation and sharing of best practices to maximise the return on investment in these technological solutions.

There was universal concern expressed on the issue of system usability, ease of use, and reliability under the system quality dimension. This finding aligns with established principles of user-centred design and points to the criticality of developing LA tools that prioritise easy to use, intuitive interfaces that can be navigated without extensive training because they make sense. Ease of use goes hand in hand with streamlined workflows, and robust performance to bring about broad adoption and sustained engagement because the system does its job efficiently (DeLone & McLean, 2003).

Across institutions, participants highlighted the importance of understandable and accurate outputs from the

LA systems (information quality) (DeLone & McLean, 2003). This emphasis on interpretability and reliability of data reinforces the importance of joining LA implementations with data literacy initiatives and validation processes to ensure actionable insights that inform evidence-based decision-making. This literacy can be provided by training programs, as well as recruiting staff competent in data literacy. This is essential for successful implementation (service quality) (DeLone & McLean, 2003). This consensus emphasises the need for a comprehensive capacity-building strategy that includes not only technical training but also the cultivation of a LA culture that promotes data-driven practices and continuous professional development.

Finally, it was generally believed by participants that LA could be used for activities like identifying at-risk students and course redesign.

Overall, this convergence of opinions reflects the potential of LA to enhance student success, optimise curricula, and inform pedagogical innovation, thereby positioning these tools as catalysts for institutional transformation and improved learning outcomes.

Divergent factors

There was a noticeable degree of variance between the specific LA tools and systems implemented across the five universities. The technical solutions adopted by each was unique to each, highlighting the absence of a uniform approach. Given this variation, some effort needs to be put in to arrive at a nuanced understanding of institutional contexts, capabilities, and objectives which can then be used to inform the selection and tailoring of LA platforms.

One notable difference is that some universities had a centralised approach, while others had a decentralised implementation that functioned at the organisational unit level, i.e. school or department. We consider that this reflects the complexity of organisational structures and decision-making processes within HEIs. Implementation project teams or departments set up at the whole of university level would likely produce a centralised solution, while projects set up at the unit level will be decentralised. This dichotomy points to the need for governance frameworks that balance institutional coordination with localised autonomy.

The level of maturity and experience with LA systems differed, with some being more advanced than others, suggesting that HEIs are at varying stages of the LA adoption lifecycle. This gap in maturity levels suggests a need for tailored capacity-building strategies and knowledge-sharing processes that can facilitate peer learning and accelerate the diffusion of best practices. Furthermore, participants had varying degrees of understanding of what constitutes a Learning Analytics system. This points to a possible lack of consensus on the conceptual boundaries and scope of the emerging field of LA. It is desirable that staff develop a shared vocabulary with clear guidelines to bring about clear communication and collaboration among stakeholders.

Data ethics policies varied among universities, with few case study participants addressing the issue. One institution noted students' discomfort with feeling evaluated. The question of data ownership and control influenced learning analytics implementation.

Observed patterns

Regional universities (one and three) had a stronger focus on online and distance education, potentially driving their adoption of LA. This observed pattern aligns with the recognised potential of LA to enhance the quality and effectiveness of remote and technology-mediated learning experiences. This helps to confirm the strategic relevance of these tools for institutions catering to geographically dispersed student populations.

Metropolitan universities (four and five) appeared to have more resources and research intensity. This is likely to influence their use of LA. This pattern suggests a potential correlation between institutional resources, research orientation, and the adoption of innovative educational technologies. This has implications for the need for targeted funding mechanisms and incentive structures for equitable access and adoption across diverse institutional contexts. These larger and more complex institutions also faced greater challenges in implementing LA systems consistently across different schools or departments. There are inherent complexities when scaling technological solutions within decentralised organisational structures, necessitating robust governance frameworks, cross-functional collaboration, and change management strategies.

Universities with a higher proportion of underrepresented student populations (one, two, and three) expressed a greater need for LA to support student success and retention. This pattern points to the potential of LA as a positive influence promoting equity, diversity and student support.

Actionable insights

Based on our comparative analysis, we derive the following actionable insights:

- Establish a shared conceptual foundation for the nature and scope of LA systems that is understood by stakeholders. This shared understanding is a pre-condition for being able to align stakeholder expectations and develop implementation strategies. We characterise it as a consensus building exercise from which constructive alignment of objectives can be achieved. Drachsler & Greller (2012) believe stakeholders should be consulted as they are the contributors and beneficiaries of LA systems.
- LA systems must be user-friendly and reliable. Unless the user experience is intuitive, if not satisfying to use, the system is unlikely to succeed regardless of how functional it might be (Delone & McLean, 1992). The system must also be able to integrate with existing workflows and have robust performance metrics available on demand (Pushparaj et al. 2023).
- Stakeholders must have appropriate data literacy skills training. Only then will they be able to interpret and action the analytical insights thus gained. Stakeholders cannot action the results of data unless they have the skills to do so. They can also be overwhelmed by data (Gray et al. 2022). In time, this will create a data-driven decision-making culture.
- A ‘top-down’ managerial commitment that makes it clear that achieving a high functioning LA system is a priority, not a ‘nice to have’ that starves for want of resources. Then a fully functional institutional strategy for LA can be developed which aligns with policy. HEIs need to commit to a LA implementation strategy that informs policy (Sclater, 2017).
- Transparent ethical principles must be established embedded in an appropriate governance framework for data use and privacy protection (Gray et al. 2022). HEIs have a right to protect its students and increasingly a society that has become more litigious (Gray et al. 2022). This will enable trust in the system to be built over time.
- Tailoring LA implementations to the specific institutional context, student demographics, and unique needs of the institution is essential if it is to be seen as relevant and useful by stakeholders (Gašević et al. 2015).
- Establish a reiterative, continuous improvement cycle that responds constructively to emerging challenges, and finds new and more efficient ways to derive value from the system. Part of this process will be to take heed of user feedback and stakeholder insights (Gray et al. 2022).

Conclusion

This comparative study has identified factors that contribute to the successful implementation and positive impact of LA initiatives, at least as far as this can be deduced from a study of five Australian universities that differ in demographic composition.

It is critical that LA systems be user-friendly and reliable. Stakeholder must have been trained with appropriate data literacy skills. There must also be clear policies and ethical frameworks that inspire trust. It is not yet clear how to translate higher education’s obligations regarding data protection into analytical practice, or how to implement the ethical principles of confidentiality, respect, transparency and informed consent in technical and pedagogical practice. Our findings emphasise the importance of aligning LA initiatives with institutional contexts, student demographics, and their unique needs.

As institutions negotiate the complex nature of LA, the insights gleaned from this study offer a roadmap for informed decision-making and strategic planning. By adopting a holistic approach that aligns technological implementations with organisational change management and stakeholder engagement, institutions can unlock the potential of LA, driving student success, optimising curricula, and allowing data-driven decision-making.

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