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Technology acceptance barriers to learning analytics adoption: Implications for inclusive education

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Learning analytics (LA) systems has potential to create inclusive educational environments supporting diverse learners in higher education. However, successful implementation depends on user acceptance by academic staff and administrators. This study examines factors influencing LA adoption in Australian universities through the Technology Acceptance Model (TAM). Using qualitative case study methodology, interviews were conducted with twenty-three participants across five demographically diverse Australian universities. Template analysis examined data according to TAM's core constructs: perceived usefulness, perceived ease of use, attitude towards use, behavioural intention, and actual system usage. Findings reveal that while participants recognised LA's potential for evidence-based decision making and personalised learning support, adoption was hindered by system complexity, data quality issues, and inadequate training. Power users demonstrated LA's capacity to enhance inclusive teaching through tailored interventions for at-risk students. Institutional barriers including fragmented systems, access restrictions, and policy constraints limited widespread adoption. Results suggest successful LA implementation requires user-centred design, comprehensive training, and institutional support structures. These findings thus provide practical insights for universities seeking to leverage learning analytics as inclusive technology promoting equitable educational outcomes.

Keywords: learning analytics, technology acceptance model, inclusive education, higher education, qualitative case study, educational technology adoption

Introduction

Learning analytics promotes inclusivity by providing personalised insights that help identify at-risk students, accommodate diverse learning styles, and ensure equitable educational outcomes across different demographic groups. If said technology is to enable learners to be better learners, the technology itself must be accepted by its users. As learning increasingly shifts towards digital and data-driven approaches, the data that is generated within digital learning environments can offer students, instructors, administrators, and student support services a range of valuable and actionable insights (Khalil et al., 2018). The adoption and use of LA tools can lead to better decision-making taking place in Higher Education Institutions (HEIs) which affects all learners (Mukred et al., 2024).

TAM (Technology Acceptance Model) directly addresses why learning analytics adoption succeeds or fails. TAM theory holds that perceived usage beliefs determine individual behavioural intentions to use a specific technology. The model's core constructs—perceived usefulness and perceived ease of use (Herodotou et al., 2019)—explain learning analytics challenges perfectly. Educators need to see clear value in student data insights and find systems simple enough to integrate into existing workflows. TAM is the instrument by which

predictions can be made about whether or not some new technological tool is going to be adopted helping institutions plan successful implementations despite technical sophistication not guaranteeing user acceptance.

The Technology Acceptance Model (TAM) (Figure 1) is an adaptation of Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1975; Ajzen,1991). It was developed to understand the link between external variables such as user acceptance and the use of systems in a workplace (Davis & Venkatesh, 1996). The application of the TAM model as applied to information systems research is a well-researched area. TAM has been proven to be one of the most effective models in the information systems literature for predicting user acceptance and usage behaviour (Davis & Venkatesh, 1995), from the original concept developed by Davis (1985) to applications using extensions of the model (Ballantine et al., 1996; Seddon, 1997; Garrity & Sanders, 1998; Rawstorne et al., 2000; Xia & Lee, 2000). The Learning Analytics Assessment model (LAAM) has also been developed as a framework to assess whether LA tools and practices are effective, ethical and meaningful for learners (Rienties et al., 2018).

The model was initially developed under contract with IBM Canada in the mid-1980s, where it served as a tool to assess the market potential of various innovative PC-based applications of that era. According to the model, the design features of a system, training, computer self-efficacy, user involvement in design and the implementation process are said to influence behavioural intention to use and ultimately effect perceived usefulness and perceived ease of use (Davis, 1985).

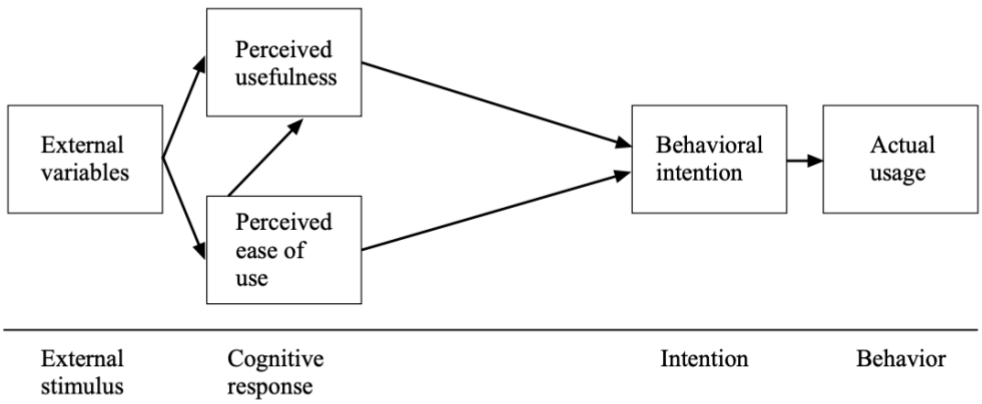

Figure 1: Technology Acceptance Model (Davis, 1985, p. 109)

An extensive body of research has been dedicated to extending the TAM model. Some researchers have introduced other factors to the model, such as subjective norms, perceived behavioural control, and self-efficacy (Hartwick & Barki, 1994; Mathieson et al., 2001; Taylor & Todd, 1995). Other work has introduced additional belief factors from the diffusion of innovation literature. These factors include factors such as trialability, visibility, or result demonstrability (Agarwal & Prasad, 1998; Karahanna et al., 1999; Plouffe et al., 2001). Other researchers have introduced external variables or moderating factors to the two major belief constructs (perceived usefulness and perceived ease of use). These include factors such as personality traits and demographic characteristics (Gefen & Straub, 1997; Venkatesh, 2000; Venkatesh & Morris, 2000) (see Figure 2).

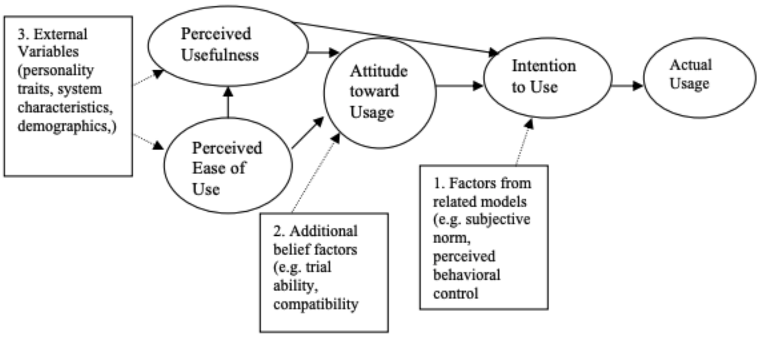

Figure 2: The Extensions to Technology Acceptance Model (Adapted from Wixom & Todd, 2005, p. 87)

A growing body of research uses TAM and its use in explaining teachers' uptake of educational technology (Sumak et al., 2011; Teo & Zhou, 2016). Although, these studies fail to address factors such as culture, education, training, learning abilities and stakeholders in their analysis but rather present statistics on perceived usefulness, perceived ease of use, behavioural intention, and usage behaviour. Although the model has been extensively validated (quantitatively) over the years, it has only proven (empirically) to successfully predict approximately 40% of a system's use (Ajzen & Fishbein, 1986). Significantly fewer qualitative studies exist compared with quantitative studies.

The Technology Acceptance Model and Learning Analytics

The literature that relates to both technology acceptance and LA is increasing in the context of HEIs implementations (Mavroudi et al., 2021). Shorfuzzaman et al., (2019) use TAM to examine the role of data analytics in the cloud in supporting LA in a mobile learning environment. This empirical study identifies important factors such as perceived usefulness and personal innovativeness as well as external factors that impact on mobile learning. The learner's readiness to adopt mobile learning is assessed using TAM. Another study by Herodotou et al., (2019) used some principles of TAM in conjunction with academic resistance models to look at whether teachers can have a positive effect on students' performance with predicative LA. These authors used a mixed methods approach to the research which indicates the need for qualitative work to be performed in this area.

While TAM is a useful model which can help to understand and explain use behaviour in information systems implementations, it needs to be integrated into a broader model that considers both human and social change (Legris, et al., 2003). The authors also found that TAM measures actual variance in self-reported use not system use (Legris, et al., 2003). Davis and Venkatesh (1995) report on the biases of TAM and conclude that researchers need to have both a clear theoretical definition on the outset of the research and to carefully select items that measure the TAM model constructs. Researchers in psychology and TAM have suggested that the user's intention to use IT is the single best predictor of actual system usage (Davis & Venkatesh, 1995). Characteristics that are lacking from TAM appear to be covered in new adaptations of the model, including testing the model's robustness, the ability to suit different contexts such as applying TAM to the Internet of Things, and to students' intention to use an online education platform in China (Zhou et al., 2022; Liu et al., 2022). The modifications also address different contexts such as gamification, e-learning, user-centric framework design of e-learning solutions and social networks (Leso & Cortimiglia, 2022). Much of the research using TAM has focussed on the use of information technology within business settings rather than HEIs, with their attendant problems.

Recognising the limitations of applying generic TAM to learning analytics contexts, Ali et al. (2013) developed the Learning Analytics Acceptance Model (LAAM). This model extends TAM by incorporating education-specific factors such as academic workload, institutional support, and pedagogical beliefs that influence educators' decisions to adopt LA systems. LAAM addresses a critical gap in TAM by considering the unique challenges educators face when integrating data-driven tools into their teaching practice. The LAAM model was inspired by TAM to understand how LA as a specific tool affected adoption beliefs by university educators (Rienties et al., 2018). It also aimed to understand the user's readiness for LA system use. Mavroudi et al., (2021) conducted a study based on the TAM examining the teacher's perspective on using LA in teaching as well as policy making. The participants views were moderate in terms of a wiliness to be ready to use an LA tool. This study used the TAM model.

There is currently a limited body of research that examines Learning Analytics (LA) within the Technology Acceptance Model (TAM) literature, with only a few emerging studies applying the Learning Analytics Assessment Model (LAAM). This study therefore seeks to apply TAM as an initial framework for analysing the collected data, with the aim of exploring how Learning Analytics can support inclusive learners. Future research may build on this by evaluating the applicability of LAAM in advancing inclusivity in learning contexts.

Methodology

A case study methodology was applied across five demographically diverse Australian universities. Case studies can generate insights that other methods may not reveal (Rowley, 2002). Comparing multiple cases strengthens the validity and generalisability of the findings (Rowley, 2002; Yin, 2013). This methodology is particularly valuable for exploratory research in areas with limited prior knowledge, enabling investigation of real-world settings and cultural factors (Järvinen, 2001; Yin, 2011). Participants were recruited through a random sampling

method. The recruitment process was time-consuming, as it required formal approval from a Deputy Vice Chancellor (DVC) or an equivalent authority at each institution. Each university provided a primary point of contact, through whom participants were identified. Interviewees held positions that involved direct engagement with the Learning Analytics (LA) system, either through teaching, supporting academic staff, or fulfilling management responsibilities. Interviews were conducted via an online platform face to face and transcribed with the assistance of sonix.ai. Ethics approval was granted by the researcher's university and each of the participating universities.

An interpretivist approach was adopted, recognising reality as socially constructed and understood through individuals' interactions withing broader 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 TAM model (Davis, 1985), based on theoretical readings. The data was then analysed and organised into a scheme using these codes (Blair, 2015; Schwandt, 2014). Template analysis was used to systematically analyse qualitative data by starting with theory-driven codes from the TAM model and then refining those codes through engagement with the data. This approach allowed the researchers to maintain theoretical grounding while remaining responsive to the nuances of participants' experiences (Blair, 2015; Schwandt, 2014).

The interview protocol of 32 questions was developed based on qualitative investigations (Ojo, 2017; Holsapple & Lee, 2006; Wang et al. 2008) and categorised according to the TAM model's factors that influence a person's decision to adopt technology, perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1985).

University case studies

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

- University One, situated in an agricultural region, specialises in online programs, and has built a strong reputation for quality despite its remote location, with a significant online student enrollment.

- University Two serves 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, acknowledged leader in online service delivery, caters for 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-focused 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 metropolitan city (Clark & Tuffley, 2023).

Qualitative Results

The TAM model (1985) categorised themes from interviews across five diverse Australian university campuses. After obtaining ethical consent, three to five participants were randomly selected from each university, totaling twenty-three participants. Recruitment procedures varied: some universities used key personnel to facilitate volunteer recruitment, while others followed strict ethical protocols. Participants included managerial staff, instructional faculty, LA support staff, user experience designers, and data scientists. Initial interviews explored LA systems implemented at respective universities.

Data was analysed using the TAM's core constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Towards Use (ATU), Behavioral Intention to Use (BI) and Actual System Usage (AU) (Davis, 1985).

Perceived Usefulness (PU)

Staff valued data supporting pedagogical decisions, such as identifying ineffective lecture formats and correlating video views with student success. Although systems often measure access rather than engagement, staff found value in metrics like video replays or resource access patterns. These forms of data were perceived by participants as more meaningful in shaping the design of course content and delivery. Although some participants like a Senior Lecturer in Education from University five, cautioned against making direct inferences solely based on learning analytics data, as students may not be engaging with the resource as the academic thinks, *And a number of them have come back to me and said, I just make cups of tea and, you know, I like and do my dinner and hang out the washing while I'm listening to lectures*. Custom reports were more useful than generic dashboards, especially when tailored to specific academic needs.

Perceived Ease of Use (PEOU)

LA systems varied from overly complex due to information overload to simple and clear. As expected, academics with high data literacy found systems easier to use, while others relied on support staff or avoided the LA systems entirely. In one example of use, an academic from university three who relied heavily on learning analytics, though all data access and generation were facilitated by a dedicated support staff member. Training, which is recognized as a critical factor in successful system implementations, improved ease of use, particularly when integrated during implementation phases. Possessing data literacy emerged as a significant finding from the study, highlighting its important role in understanding and interpreting data.

Attitude Towards Use (ATU)

Participants' attitudes toward LA systems appeared strongly influenced by their perceived usefulness and ease of use experiences. Those who successfully used LA for student interventions developed positive attitudes, while academics experiencing system complexity or data quality issues expressed scepticism. Participants saw the potential LA systems have in enhancing the capacity for staff to identify and support at-risk students. Like the Deputy Director of Student Administration at University one, *So, one example of that in practice is we work from the learning management system. We would extract a report of all students who didn't submit their first* *assessment. We would put that into our outreach platform, and it would generate that list of students who may be at-risk and would get a proactive assessment then and follow up not only proactively using the data. That's in retrospect, but that would trigger an assessment or risk assessment and a contact from a student relationship officer who might see some of those students.* Institutional support and successful peer examples of using LA to support at-risk students seemed crucial for fostering favourable attitudes toward adoption.

Behavioral Intention to Use (BI)

Participants showed a variety of different use cases. Many academics preferred requesting data rather than using LA systems directly, indicating gaps between intention and actual use. A participant from university three describes her skills as quite rudimentary, *I'm not a systems person at all. I'd struggle with any system I even*

struggle with pivot tables. Some engaged in system avoidance, finding LA too complex or irrelevant, preferring human-mediated data access. A small percentage of power users existed. An electrical and biomedical engineering lecturer from University Four stated *But, you know, I'm an engineer, so if I want that data, I can generate that myself pretty easily*. These users were highly engaged academics who used LA extensively, embedding it in courses and redesigns and for the purpose of identifying and supporting students.

Actual System Usage (AU)

Many interviewed participants used LA systems, possibly explaining their willingness to be involved in this study. Some relied on support staff for ad-hoc reports. Systems were fragmented across universities, each having unique setups—some proprietary, others user-built—complicating consistent campus-wide use. At university

three, if students fail to submit an assignment, they have a code assigned to them that indicates potential risk. The code flags a student for the teaching staff member to monitor that student. There are also reports that can show which resources a student has accessed and engaged with and the frequency within a time frame. This university also uses a 'check-in' survey that can inform teaching practices going forward. Although the response rate of these surveys can be an issue. A participant who was in the position of Dean, Student Retention commented, *I think that's probably the big risk in any type of analytics, is letting it lead your decision-making instead of being something that enhances your decision*. Institutional barriers including access restrictions, policy constraints, and organisational restructuring hindered widespread adoption.

Discussion

Given that LA system implementations are institution wide, system support is needed across the whole university. There can be limitations in terms of LA system support as support units need to service the staff of an entire university. Therefore, stakeholders need to be engaged at different levels throughout the LA implementation process, from managers to faculty heads, and importantly the users of the system. Technical specialists are required to support LA systems due to the complex nature of institutional data (West et al., 2015). At a minimum these requirements must be met. Four of out five universities had established LA support units to support staff in the use of the LA system which shows they had the beginnings of adequate infrastructure in place. Another important factor to consider is where teaching staff rely solely on data generated from LA systems. It is essential that this practice does not happen. Data generated from LA systems should be used as a decision-making tool. Participants in the study cautioned that LA data could guide decisions made around the learning and teaching process as a decision-making support tool but must not be relied upon as the only source of data. Being able to accurately interpret data enables educators to understand where learners are in their learning process and being able to set goals and learning intentions for the next steps of the learning process (Victoria State government Department of Education, 2021).

Having noted the limitations above, successful LA adoption directly supports inclusive education by enabling academics to identify and assist at-risk students from diverse backgrounds. Power users demonstrated how data-driven interventions address specific needs of first-generation, low-socioeconomic, and mature-age learners across participating universities.

Learning analytics in higher education remains conceptually ambiguous, with ongoing debate over whether it should be understood as a technological system or educational process. This uncertainty reflects broader questions about LA's function within pedagogical contexts. Universities are perceived as lagging behind commercial sectors in analytics sophistication, limiting their ability to leverage data effectively. Technical barriers include fragmented, inconsistent datasets from multiple vendors. Despite challenges, LA tools offer inclusive potential through personalised learning strategies tailored to individual needs and abilities.

Examining TAM in relation to LA offers significant benefits for Australian universities navigating digital transformation. TAM provides a structured framework for understanding how staff perceive and adopt LA tools, focusing on perceived usefulness and ease of use. This is especially relevant where universities face

varied digital literacy levels, ethical considerations around student data, and needs for evidence-based teaching practices. TAM helps institutions identify adoption barriers, tailor professional development, and design user-friendly systems aligned with educators' needs while maximising LA impact through data-informed decision-making and inclusive education strategies.

This study was limited to Australian universities, potentially restricting transferability to other contexts. Twenty-three participants may not capture the full spectrum of academic perspectives. Focus on TAM constructs may have overlooked other factors influencing LA adoption in diverse settings. Universities must prioritise user-centered design and comprehensive training to ensure LA systems serve inclusive goals. Support structures should address diverse student population needs. Professional development should emphasise how LA identifies and supports at-risk students from various backgrounds.

Learning analytics has the potential to foster inclusivity by delivering personalised insights that identify at-risk students, support diverse learning styles, and promote equitable educational outcomes across demographic groups. However, for such technology to truly empower learners, it must first be accepted and embraced by its users. As education continues to shift toward digital and data-driven approaches, the information generated within learning environments offers students, instructors, administrators, and support services a powerful source of actionable insights to enhance learning and teaching (Khalil et al., 2018).

Future studies should explore LA adoption across different cultural and educational contexts beyond Australia. Research examining relationships between implementation success and inclusive outcomes would strengthen evidence. Longitudinal studies tracking adoption patterns could reveal sustainability factors. Future research could incorporate the LAAM extension to the TAM model to explore whether the additional factors influence technology acceptance.

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