ASCILITE 2025
Future-Focused:
Educating in an Era of Continuous Change

Enhancing student retention through predictive analytics and outreach: A case study in early intervention in online postgraduate studies

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This paper presents a case study of a predictive analytics pilot aimed at improving student retention in postgraduate online learning. By leveraging Learning Management System (LMS) engagement metrics, students who had not accessed or submitted their first assessment at least five days before the due date, were flagged for early outreach. A tiered human-led interventions model via email, phone, and SMS were triggered to provide personalised support. The pilot was implemented across 12 postgraduate subjects in 2025 and benchmarked against 2024 cohorts. A 1.9 percentage point improvement in dropout rate was observed, equating to approximately 32 additional students retained. These findings highlight the practical value of low-complexity, data-informed interventions and the role of AI-human synergy in supporting online learners. This pilot demonstrates a scalable approach to integrating predictive analytics with personalised support in fostering adaptable learners and improving student outcomes, particularly in resource constrained settings.

Keywords: predictive analytics, student retention, learning analytics, early intervention, adaptable learners, AI-human synergy, case study

Introduction

Student retention remains a persistent challenge in online learning environments. Research has long demonstrated that withdrawal is often influenced by both academic and social disintegration (Tinto, 1993). In online contexts, factors such as isolation, workload, and external commitments further exacerbate these challenges (Kember, 1995). Many students silently disengage early, with limited interaction until after critical milestones (e.g., first assessment submission or Census date) have passed. Institutions are increasingly turning to proactive, scalable approaches that enable early, personalised support. Traditional models often rely on broad or manual outreach, which may fail to detect individual needs in time. Predictive analytics using LMS data is a promising tool for early detection of at-risk students and for triggering timely, data-informed interventions (Baneres et al., 2024; Jayaprakash et al., 2014; Arnold & Pistilli, 2012).

This paper presents a case study of a pilot initiative aimed at improving student persistence by identifying early disengagement and enabling human-led outreach. It explores the fusion of data analytics with personalised support practices, using key metrics, such as assessment engagement and participation, to flag behaviours that may prevent students from reaching critical milestones (e.g., first assessment submission or census date). By identifying these risks early, the initiative enabled timely intervention through personalised, human contact.

This pilot study addresses the following question: *Can a low-complexity, LMS based predictive analytics model, combined with human-led outreach, improve student retention in online postgraduate subjects?*

Method

This pilot draws on Tinto's (1993) model, which emphasises the importance of academic and social integration as drivers of retention. In online learning, where informal integration opportunities are limited, timely and personalised support acts as a mechanism for digital social connection. The intervention also aligns with the "human-in-the-loop" approach to learning analytics (Prinsloo & Slade, 2017), where data triggers inform, rather than replace, human decision-making and student support.

The pilot adopted an action research design (Kemmis & McTaggart, 2000), supporting implementation and refinement of engagement strategies based on student behaviour and feedback.

The intervention was delivered through a partnership between a higher education provider and a private student support agency. A predictive engagement metric was developed using LMS data, flagging students as 'at risk' if they had not accessed or submitted their first assessment at least five days before the due date. This threshold was based on prior research showing early assessment engagement correlates with persistence, and that non-submission strongly signals potential dropout (Bañeres et al., 2023). Students with weekly LMS usage under seven hours, derived from a midpoint benchmark of 15 recommended study hours per week per subject were also considered for outreach.

Once flagged, students were contacted through a tiered outreach process: an initial personalised email, followed by phone and SMS outreach for non-responders. Messages were tailored to subject's context, tone, and engagement history, and delivered by trained support staff. The approach was informed by models that emphasise the importance of early, personalised, non-academic support, personalised support to address motivational, navigational and or time management challenges (Rotar, 2022; Seery et al., 2021).

The pilot was implemented across 12 postgraduate subjects during Terms 2 and 3 in 2025, involving a total enrolment of 1,681 students. Dropout rates were benchmarked against corresponding 2024 cohorts to evaluate impact of the intervention in the same subjects

Ethical considerations: This study used de-identified, aggregated LMS data collected retrospectively for quality assurance. No identifiable student information or academic results were used, and the analysis had no impact on student grades or progression. All data was collected after the teaching period and was not linked to individual student outcomes or academic performance. Limitations include the absence of a control group and potential variability across subjects, which will inform future refinements to the model.

Results

The intervention's impact was examined by comparing student dropout rates in 2025 to corresponding 2024 cohorts across 12 postgraduate subjects. All data was analysed retrospectively using de-identified, aggregated LMS records for post-teaching quality assurance process.

Term 2 Findings
In Term 2, four core STEM subjects were monitored. Table 1 below presents dropout rate comparisons, showing an average decrease from 21% in 2024 to 18% in 2025, equating to 20 additional retained students.

Three of the four subjects showed reductions in attrition, with the most notable improvement in Subject 4 (-8 percentage points). Subject 2 recorded a modest increase (+2 percentage points), which may reflect normal cohort variation.

Table 1
Dropout Rate Comparison – Term 2 2024 vs 2025

Subject	Students enrolled day 1	Students enrolled post-census	Drop rate T2 2024	Drop rate T2 2025	Change
Subject 1	99	81	22%	18%	-4p.p.
Subject 2	181	150	15%	17%	+2p.p.

Subject 3	282	233	20%	17%	-3p.p.
Subject 4	100	77	31%	23%	-8p.p.
Total	662	541	21%	18%	-3p.p.

Note. p.p. = percentage points. Dropout rate calculated based on enrolment post-census / students enrolled day 1

Term 3 Findings

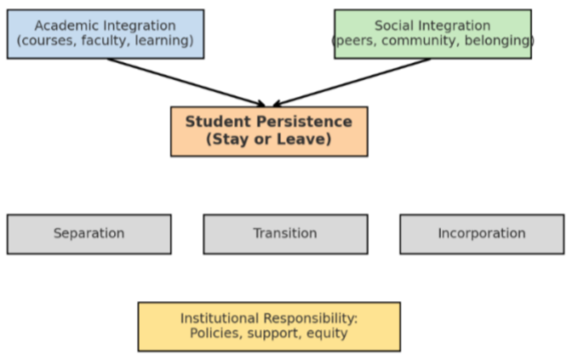
In Term 3, the pilot was extended to six further subjects. As shown in Table 2, the overall dropout rate fell from 19% in 2024 to 17.5% in 2025. yielding modest gains. As in Term 2, three subjects in Term 3 demonstrated reductions in attrition, most significantly Subject 5 (-23p.p.) and Subject 3 (-13p.p.). However, Subjects 1, 2, and 4 experienced small increases in dropout rates. At this early stage, it is not possible to attribute these changes to a single cause. Possible contributing factors may include cohort characteristics, staffing changes, or fluctuations that fall within the expected range of variation.

Table 2
Dropout Rate Comparison – Term 3 2024 vs 2025

Subject	Student enrolled day 1 - 2025	Students enrolled post-census 2025	Drop rate T3 2024	Drop rate T3 2025	Change
Subject 1	201	163	15%	19%	+4p.p.
Subject 2	198	154	17%	22%	+5p.p.
Subject 3	128	105	31%	18%	-13p.p.
Subject 4	231	187	18%	19%	+1p.p.
Subject 5	175	161	31%	8%	-23p.p.
Subject 6	86	70	25%	19%	-6p.p.
Total	1019	840	19%	17%	-2p.p.

Note. p.p. = percentage points. Dropout rate calculated based on enrolment post-census.

During the two-week outreach period, over 450 students were contacted based on the predictive risk indicators. Of these, 129 students, or approximately 29%, provided feedback or engaged with support. Across both terms, the overall dropout rates decreased by 1.9 percentage points, compared to 2024, resulting in 32 additional students retained.



'Diagram showing Academic Integration and Social Integration leading to Student Persistence and Retention'
Figure 1. Conceptual representation of Tinto's Student Integration Model

Discussion and implications

AI and human synergy – human-in-the-loop learning analytics

The pilot demonstrated how a low-complexity predictive tool, embedded within a 'human-in-the-loop' model, can support early-intervention in online learning. The tool acted as a decision-support mechanism enabling timely, meaningful human outreach. This reflects a trend where AI-adjacent tools complement rather than replace human support roles (Prinsloo & Slade, 2017). The assessment engagement trigger aligns with established early alert practices and supports evidence of strong links between assessment activity and student persistence (Bañeres et al., 2023).

Findings show institutions can use learning analytics without large-scale AI infrastructure or complex models. Even low-complexity tools, combined with human judgement and targeted support, can improve student retention. This offers a practical pathway for resource-constrained or smaller-scale providers to improve retention.

Re-engaging learners

The intervention helped students reconnect by addressing challenges before they became entrenched. Consistent with previous research, early, personalised outreach — particularly targeting non-academic issues such as motivation, navigation, or time management — can play a critical role in supporting persistence. Tailored communication, proactive contact, and access to support services contribute meaningfully to improving student retention in online settings (Seery et al., 2021; Walsh et al., 2020).Furthermore, students appreciated speaking with a student support specialist and addressing other issues that otherwise would not have been addressed. For example, several students requested extra support with personalised study plans, clarification on enrolment policy and guidelines, and assistance navigating the LMS.

Findings suggest that online retention strategies should not focus solely on academic interventions. Embedding proactive, structured, personalised outreach early — particularly before key milestones like the first assessment — may help re-engage students at risk of silent withdrawal. This highlights the value of collaboration between analytics, support services, teaching teams and course designers.

Design reflections

The pilot confirmed that simple indicators such as LMS access patterns and early assessment engagement can be reliable early warning signals. Weekly monitoring cycles allowed interventions to occur within a meaningful timeframe, a principle supported by both the ISSPM framework and the literature on early alerts (Rotar, 2022; Ncube & Ngulube, 2024). Future work will incorporate additional indicators such as login frequency and page interaction to create a layered risk profile and a risk propensity model. Observations from support staff, recorded as part of routine service delivery, suggested that the first assessment may act as a natural decision point for student engagement. This suggests an opportunity for learning designers to structure early assessments as confidence-building tasks — not only to gauge academic readiness, but also to support re-engagement for those at risk of silent withdrawal.

Conclusion and next steps

This case study illustrates how predictive analytics can serve as a springboard for empathetic and targeted human-led support in online learning environments. While not a fully autonomous AI system, the pilot model leveraged data to trigger students at risk and initiate timely outreach. The modest but meaningful reductions highlight that low-complexity, data-informed interventions can be scalable and adaptable to institutional constraints. It offers a replicable framework for institutions seeking to operationalise learning analytics to foster adaptive and supported online learning environments. The pilot reinforces the viability of combining predictive tools with personalised support to enhance student retention. These findings strengthen the case for institutional invest in agile learning analytics paired with trained support personnel, rather than relying solving on high-cost or complex AI infrastructure.

Theoretically, the study builds on Tinto's model (1993) of student persistence by demonstrating that early, personalised intervention, prompted by behavioural data, can support both academic integration and personal engagement in online learning environments. It also aligns with human-in-the-loop learning analytics principles, where data supports, not replaces, human judgement. These insights support a broader shift towards more student-centred retention strategic digital education landscape.

Future work will explore additional behavioural indicators, variations across disciplines, and the long-term impacts of early outreach on learning outcomes and course progression. Further refinement of the predictive model and integration into wider institutional strategies will inform next steps in building adaptive, equitable online learning ecosystems.

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