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A learning analytics-informed continuation programme and student continuation: A mixed-methods quasi- experimental study

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Abstract

Improving student continuation is a priority for higher education institutions seeking to improve student outcomes and address inequalities in their settings. This study evaluated a learning analytics-informed continuation programme implemented over three academic years at a UK university. The programme used a predictive model to identify first-year undergraduate students at risk of discontinuation, continuously monitored their engagement, and initiated proactive support when specified disengagement thresholds were met. A convergent mixed-methods design was used. The quantitative strand analysed anonymised institutional data from 2,983 students across 2022/23, 2023/24, and 2024/25, using propensity-score matching and doubly robust augmented inverse probability weighting to estimate the association between programme identification and subsequent continuation. The qualitative strand drew on semi-structured interviews with 12 course leaders to explore perceived mechanisms of impact. Quantitative findings varied by year. No statistically reliable improvement in continuation was observed in 2022/23, when the intervention was delivered through support-services-led contact, or in 2023/24, when delivery was interrupted and redesigned. In 2024/25, the first full year of a course-leader-led model, identification for the programme was associated with a statistically significant increase in continuation of approximately 10 to 13 percentage points. Qualitative findings suggested that course leaders valued the programme for identifying risk, prompting timely conversations, and enabling contextualised support, while also emphasising the need for coordinated action across academic and professional services teams. The study highlights the importance of pairing predictive insight with sustained, relational, and context-sensitive intervention. Findings have relevance for institutions seeking to strengthen learning analytics-informed approaches to support students continuing their studies.

1. Introduction

In UK higher education, improving continuation rates is both a regulatory priority and an equity imperative (Office for Students, 2022, 2023). The Higher Education Statistics Agency defines continuation as the proportion of students who have continued their studies, qualified, or transferred to another higher education institution in the UK (Higher Education Statistics Agency, n.d.). This outcome measure highlights persistent disparities for student groups that have historically faced unequal opportunities, which motivates many institutions to develop scalable approaches that identify disengagement early and connect students to timely, appropriate support as a means to increase continuation rates. Learning analytics (LA) has emerged as one prominent response to this challenge, promising to translate routinely collected data into actionable insight about engagement, risk, and support needs (Wong, 2017).

1.1. Learning analytics in higher education

LA generally refers to the collection, analysis, and presentation of learner-related data to understand and improve learning and the conditions in which it occurs (Siemens, 2013). In practice, LA commonly draws

on institutional systems such as the virtual learning environment (VLE), assessment scores, attendance monitoring, and other interaction traces to build dashboards, flags, and predictive models that support staff decision-making

Across the wider literature, LA applications typically combine two elements: insight (identifying patterns associated with risk and success) and action (using those insights to trigger structured outreach and support). Milliron et al. (2014) characterise this as 'insight and action analytics', arguing that predictive models are only valuable when coupled with intentional intervention workflows and iterative refinement. Empirically, studies have demonstrated that early performance indicators and engagement traces can predict subsequent outcomes, and that targeted feedback can improve attainment-related indicators, particularly in large foundational courses (Espinoza & Genna, 2021; Jayaprakash et al., 2014). However, the translation from prediction to improved continuation is not guaranteed. The effects appear to depend on the timing, salience, and credibility of messages, as well as on the availability of human support and institutional capacity to respond.

1.2. Interventions focussed on improving continuation

LA-informed interventions to improve continuation typically follow the common insight and action sequence: identifying students using behavioural and/or assessment indicators, delivering an intervention (often a message, advising contact, or structured academic support), and monitoring changes in engagement and progression. In experimental and quasi-experimental studies, identification has been operationalised using combinations of early grades and VLE traces (Jayaprakash et al., 2014), 'trigger' systems based on attendance proxies and assessment scores (Dodge et al., 2015), and predictive models updated throughout delivery (Cambruzzi et al., 2015). Intervention designs range from light-touch nudges (emails and dashboards) to more intensive, staff-mediated outreach. For example, instructor-branded feedback following each assessment throughout a term improved course grades and reduced withdrawals across two years of implementation, with the largest gains observed for high-risk students (Espinoza & Genna, 2021). By contrast, some scalable email-based approaches have shown limited average effects, suggesting that minimal 'nudges' may be insufficient for many students even when risk is detected accurately (Dodge et al., 2015).

The evidence base for LA-informed interventions also contains important cautions. Jayaprakash et al. (2014) reported improved grades for flagged students receiving either awareness emails or invitations to online support, yet also observed higher withdrawal rates in intervention groups, highlighting potential unintended consequences of risk messaging and the ethical stakes of false positives. More broadly, a UK-focused TASO report synthesising two randomised controlled trials at English providers concluded that there is limited causal evidence on LA-informed interventions in the UK and that additional outreach (an adviser phone call) did not measurably improve post-intervention engagement compared with email-only contact among flagged students (Summers et al., 2024). This mixed picture is consistent with findings from other LA studies, where modest improvements in intermediate online performance do not always translate into summative attainment gains, and uptake often declines over time (Hellings & Haelermans, 2022; Kim et al., 2016). Collectively, these studies suggest that LA can support earlier

identification and targeted contact, but that effectiveness depends on intervention intensity, contextual fit, and the mechanisms through which contact translates into positive student outcomes.

1.3. Research aim and questions

Given the uneven and sometimes ambiguous impacts reported in existing research, there remains a need for further well-designed evaluations that investigate the impact of LA-informed interventions on continuation. Thus, the present study aims to evaluate the impact of a continuation programme on student outcomes, integrating short- to medium-term experiences with a longer-term continuation outcome through a convergent mixed methods design. To achieve the aim, the study investigates the following research questions:

RQ1. What are the perceived implications of the continuation programme and academic-led intervention upon student engagement and outcomes?

RQ2. What is the estimated association of inclusion in the continuation programme on students' continuation rates?

The remainder of the paper describes the intervention, outlines the methods and materials used to investigate the research questions, presents the mixed-methods findings, and concludes by discussing the implications for LA-informed, continuation-focused interventions in higher education.

2. Intervention Description

The continuation programme was implemented across the academic years 2022/23 to 2024/25, with the primary objective of improving first-year student continuation and reducing persistent disparities for student groups experiencing unequal opportunities. Across all years, the programme combined early identification of disengagement with proactive outreach, with the intention of providing timely, tailored support before academic difficulties became entrenched. However, the delivery model evolved over time as the programme was refined in response to implementation experience and faculty consultation.

The programme targeted first-year students who registered to start the academic year from September each year. Students were identified for inclusion in the programme on 1 November using a learning analytics approach that did not directly include protected characteristics and instead relied on behavioural and early academic indicators. Risk predictions were generated using a Random Forest Classifier trained on data from prior cohorts, drawing on the number of modules enrolled, VLE module page visits, academic grades, and VLE quizzes recorded by 1 November each year. Following this initial identification, engagement was monitored regularly through a dashboard updated each week using the previous week's VLE engagement and class attendance data. The dashboard was reviewed to identify students whose engagement fell below pre-specified thresholds (fewer than five module page visits and/or under 50% attendance in the preceding week).

In 2022/23, the first year of implementation, the programme was delivered by support services staff, who contacted disengaged students approximately every two weeks to offer support and, where appropriate, one-to-one conversations. In 2023/24, the programme initially began in the same format but was subsequently paused while the approach was reviewed with faculty staff. Following this consultation, the delivery model changed. Rather than support services contacting students directly, relevant course leaders received a list of disengaged students weekly and contacted them to have supportive conversations, explore barriers to engagement, and facilitate access to appropriate institutional support. This revised model began in mid-March 2024, meaning that delivery was interrupted for more than half of the academic year. In 2024/25, the programme operated from November to the end of the academic year without interruption, representing the first full year of implementation using the weekly course leader contact model.

3. Materials and Methods

This study adopted a convergent mixed-methods design, in which quantitative and qualitative strands were implemented in parallel, analysed separately, and then compared during interpretation to develop an integrated understanding of the intervention's impact and underlying mechanisms (Creswell & Creswell, 2018; Morgan, 2007). The design was grounded in a pragmatic paradigm that prioritised methodological choices suited to evaluating an applied intervention in a live institutional context (Patton, 1990). In line with guidance on quasi-experimental research, the quantitative strand used a matched comparison approach to estimate the association between participation in the intervention and subsequent continuation, while the qualitative strand used semi-structured interviews to explore course leaders' perceived implications of the programme on short- to medium-term student outcomes (Gopalan et al., 2020; Office for Students, 2019). The project received full ethical approval from the University of Suffolk's ethics committee prior to conducting the study (RETH24/065).

3.1. Quantitative strand

3.1.1. Data collection

Quantitative data were obtained from an anonymised institutional dataset of undergraduate students. The analysis included students registered in the academic years 2022/23, 2023/24, and 2024/25. The sample was restricted to students at Level 4, corresponding to first-year undergraduate study. Across the three academic years, 2,983 students met the eligibility criteria, of whom 578 were in the treated group and 2,405 were in the control group. The treatment condition was defined as being identified for the continuation programme, while all other eligible students were classified as controls. Identification initiated continuous monitoring of students' engagement and made students eligible for threshold-triggered outreach throughout the academic year. Thus, treatment represented inclusion in the programme's monitoring-and-response pathway rather than receipt of outreach alone. Students who remained above the engagement thresholds continued to be monitored but did not require outreach. The

primary outcome was student continuation, operationalised as whether the student continued their studies in the following academic year.

The dataset included demographic, academic, and engagement-related covariates selected a priori for confounding adjustment. These comprised academic year, declared disability, ethnicity, subject discipline, sex, IMD quintile, entry-age group, prior engagement with assessed work or quizzes, number of modules enrolled, and total VLE unit accesses. The number of modules enrolled, and total VLE unit accesses were provided as standardised values, expressed as z-scores, and were analysed on this scale. Subject discipline was coded as STEM or non-STEM using HESA CAH subject codes. Sex, ethnicity, and declared disability were represented using binary indicators, while IMD quintile and entry-age group were represented using dummy variables. Two engagement indicators were derived from the availability of assessment and quiz data. Students with an average grade were coded as having grade data, and students with an average quiz score were coded as having quiz data.

Missing values in the standardised number of modules enrolled and standardised total VLE unit accesses were handled using multiple imputation by chained equations (Rubin, 1987). Table 1 reports the proportion of missing data for these variables across academic years. A total of 100 imputed datasets were created using a Bayesian ridge estimator with posterior draws, 20 maximum imputation iterations, median initialisation, and fixed random seeds to support reproducibility. The imputation model included treatment status, continuation status, academic year, and all the covariates.

Table 1
Proportions of missingness across the two standardised engagement-related variables.

Variable	2022/23 (n = 1106)	2023/24 (n = 953)	2024/25 (n = 924)
Number of modules	7.87%	12.07%	14.39%
VLE unit accesses	8.14%	12.49%	10.71%

3.1.2. Data analysis

As random assignment to the continuation programme was not feasible, the quantitative strand used a quasi-experimental causal-inference design based on propensity-score methods. This approach was used to approximate a counterfactual comparison group by balancing observed covariates between treated and comparison students (Rosenbaum & Rubin, 1983; Stuart, 2010). The primary estimand was the average treatment effect on the treated (ATT), interpreted as the difference in continuation outcomes for students included in the programme's monitoring-and-response pathway relative to the outcomes they would have been expected to experience had they not been included, conditional on the measured covariates and within the region of covariate overlap.

The analysis proceeded in five sequential phases. First, the analytic sample was trimmed to improve covariate overlap between treated and comparison students. Second, propensity-score matching was conducted within each imputed dataset and used to estimate the matched ATT. Third, a doubly robust

augmented inverse probability weighting (AIPW) estimator was applied as a robustness check. Fourth, estimates from the propensity-score matched and AIPW analyses were pooled across the imputed datasets. Fifth, sensitivity to unmeasured confounding was assessed using E-values calculated from the pooled risk-ratio estimates.

In the first phase, the sample was trimmed to improve common support and reduce the variance and bias of treatment effect estimates. The initial propensity-score distribution was trimmed using Stürmer-style percentile trimming. Observations were retained if their initial propensity score fell between the 5th percentile of the treated group and the 95th percentile of the comparison group (Stürmer et al., 2021). After trimming, the propensity-score model was re-estimated within the retained sample before matching.

In the second phase, propensity-score matching was conducted separately within each trimmed imputed dataset. One-to-one nearest-neighbour matching without replacement was performed on the logit of the propensity score. A caliper width equal to 0.20 of the standard deviation of the logit propensity score was used, consistent with common recommendations for propensity-score matching (Austin, 2011). To reduce dependence on the ordering of treated cases, treated observations were randomly permuted before greedy matching using a fixed seed. Following matching, covariate balance was assessed to evaluate whether the matched comparison group provided an adequate counterfactual. Balance was assessed before and after matching using standardised mean differences (SMDs). Absolute SMDs below 0.10 were interpreted as indicating good balance, while those below 0.25 were considered acceptable (Stuart, 2010). Balance was summarised numerically by comparing the mean absolute SMD before and after matching across the imputed datasets. The matched analysis then estimated the ATT as the primary treatment-effect estimate. The ATT was expressed as a risk difference in continuation between matched treated and comparison students. Matched-pair differences were used to calculate the risk-difference estimate and its standard error. A risk ratio was also estimated on the log scale, with uncertainty quantified using a delta-method standard error that accounted for the matched-pair structure.

In the third phase, a doubly robust AIPW estimator was used to assess the robustness of the matched estimates. This analysis was conducted within the trimmed sample in each imputed dataset. The estimator combined a propensity-score model with an outcome model and is consistent if either model is correctly specified (Funk et al., 2011). The propensity-score component was estimated using logistic regression. The outcome model estimated the counterfactual probability of continuation under non-identification using a random-forest classifier trained on comparison students only. Where sample size permitted, five-fold stratified cross-fitting was used, with out-of-fold nuisance predictions used to construct the AIPW ATT. The AIPW analysis estimated both the ATT risk difference and the ATT risk ratio.

In the fourth phase, estimates were pooled across the 100 imputed datasets. Rubin's rules were used to pool results for both the propensity-score matched and doubly robust AIPW analyses (Rubin, 1987). For

each estimand, the pooled estimate, standard error, 95% confidence interval, p-value, between-imputation variance, within-imputation variance, total variance, degrees of freedom, and fraction of missing information were calculated. Risk-ratio estimates were pooled on the log scale and then exponentiated for interpretation.

In the fifth phase, sensitivity to unmeasured confounding was assessed using E-values. E-values were calculated from the pooled risk-ratio estimates and their confidence intervals (VanderWeele & Ding, 2017). This was done for both the propensity-score matched risk ratio and the doubly robust AIPW risk ratio. For protective associations, risk ratios were inverted before E-value calculation. When the confidence interval included the null value of 1.00, the E-value for the confidence limit closest to the null was set to 1.00.

These analyses were conducted separately for each academic year to examine whether the estimated effect varied across years in which intervention delivery evolved. All quantitative analyses were conducted in Python using reproducible scripts (**Supplementary Material A** includes all analysis scripts and outputs).

3.1.3. Limitations

Several limitations constrained interpretation of the quantitative strand. First, propensity score methods and doubly robust estimation depended on the conditional independence (no unmeasured confounding) assumption. Therefore, unobserved factors related to both participation and continuation (e.g., prior help-seeking, motivation, or staff referral practices) could have biased effect estimates (Rosenbaum & Rubin, 1983; Stuart, 2010). Second, multiple imputation assumes that missing values were missing at random. If missingness in the data reflected unobserved disengagement or administrative processes not captured by the model, residual bias may remain. Third, restricting analyses to the region of common support improved internal validity for the overlap population but potentially reduced generalisability to students whose propensity scores lay outside the overlap region (Stürmer et al., 2010; Stürmer et al., 2021). Finally, continuation was a longer-term outcome and did not capture intermediate outcomes such as students' perceived confidence, belonging, or access to support, which could plausibly change without immediately translating into differences in recorded continuation (Gopalan et al., 2020).

3.2. Qualitative strand

3.2.1. Data collection

The qualitative strand explored course leaders' experiences of the intervention and identified perceived mechanisms linking programme components to students' course engagement and continuation. Twelve semi-structured interviews were conducted with course leaders who had been notified via the continuation programme team of students at risk of withdrawal on their course. Semi-structured interviewing was selected for its capacity to support in-depth exploration while remaining responsive to participants' narratives and priorities (Rubin & Rubin, 1995). To support accessibility, interviews were offered either in person on campus or online via synchronous audio-visual platforms, reflecting evidence

that online interviewing can facilitate rapport and disclosure comparable to face-to-face formats (Howlett, 2022; Jenner & Myers, 2019). All participants provided informed consent, and interview data were anonymised and managed in accordance with ethical and data governance requirements.

3.2.2. Data analysis

Interview transcripts were analysed using Template Analysis (TA), a flexible form of thematic analysis characterised by the iterative development of a hierarchical coding template to organise patterns of meaning within qualitative datasets (King, 2004; Brooks et al., 2015). TA views analysis as an interpretive process in which researchers construct, apply, and refine a coding template to represent salient features of participants' accounts. The interview schedule is provided in **Supplementary Material B**.

Analysis began with familiarisation followed by preliminary coding of a subset of transcripts to identify emergent ideas and their alignment with a priori concepts from relevant literature. These initial codes were then clustered and organised hierarchically to form an initial template, collaboratively developed by all researchers. This template was iteratively applied to the remaining transcripts by two researchers and refined, through adding, redefining, or reorganising codes, to ensure adequate representation of all relevant material (King, 2004; King & Brooks, 2017; see **Supplementary Material C** for the final template).

Analytic attention focused on participants' perceptions of the programme's outcomes, including exploring facilitators and barriers to student continuation, the role of intervening teams in supporting student continuation, and implications of intervention upon student course engagement and attendance. TA also enabled exploration of how participants understood the contribution of specific programme components to these experiences, with researcher interpretation treated as an integral resource in producing a coherent analytic account (Brooks et al., 2015; King & Brooks, 2017).

3.2.2. Limitations

The qualitative strand was also subject to limitations. First, interview participation was voluntary and therefore susceptible to self-selection bias, as course leaders with particularly positive or negative experiences may have been more likely to participate (Patton, 1990). Second, the qualitative interviews were conducted with course leaders within the 2025/26 academic-year, whereas the quantitative analysis examined the 2022/23 to 2024/25 student registration cohort; consequently, whilst many course leaders had experienced the programme over the years explored quantitatively, qualitative findings were used primarily to illuminate plausible mechanisms and experiences rather than to provide direct within-cohort triangulation of outcomes (Creswell & Creswell, 2018). Finally, because template analysis is explicitly interpretive, themes were presented as well-grounded analytic interpretations rather than exhaustive or purely descriptive accounts of all possible experiences of the programme.

4. Results

4.1. Quantitative strand findings

The quantitative results are presented separately for each academic year because the programme delivery model changed across implementation. For each year, results are reported in the following sequence: first, a summary of how the intervention was delivered; second, a report on covariate balance after propensity-score matching; third, the PSM estimate of the ATT, including E-value sensitivity analysis; and fourth, the DR AIPW estimate, also including E-value sensitivity analysis. Risk differences are reported as percentage-point differences in continuation between students identified for the continuation programme and comparable students who were not identified. Positive values therefore indicate higher continuation among identified students.

4.1.1. Results for the 2022/23 academic year

In 2022/23, the continuation programme was delivered by support services staff, who contacted students identified as disengaged approximately every two weeks to offer support and, where appropriate, one-to-one conversations. The analytic sample for this year included 1,106 students, of whom 115 were identified for the programme and 991 were in the comparison group.

Across the 100 imputed datasets, PSM produced an average of 56.23 matched pairs per imputation, with the number of matched pairs ranging from 52 to 65. Covariate balance improved after matching, although improvement was more modest in this year than in later years. Across covariates, the mean absolute SMD before matching was 0.134, compared with 0.111 after matching. The covariate-level matched absolute SMD means ranged from 0.086 to 0.183. This indicates that matching reduced overall imbalance, but some covariates remained above the conventional 0.10 threshold on average, suggesting that the 2022/23 matched estimate should be interpreted with some caution.

The PSM estimate suggested a small, positive association between identification for the programme and continuation. However, this estimate was not statistically significant. The ATT risk difference was 3.19pp, SE = 7.73, 95% CI [− 12.01, 18.38], p = .681. On the risk-ratio scale, the matched estimate was RR = 1.04, 95% CI [0.87, 1.23], p = .678. The E-value for the point estimate was 1.23, but because the confidence interval included the null, the E-value for the confidence-limit closest to the null was 1.00. This indicates that the observed estimate was not robust to unmeasured confounding.

The DR AIPW estimate was similar in direction and magnitude. The estimated ATT risk difference was 3.49pp, SE = 4.87, 95% CI [− 6.07, 13.05], p = .474. The corresponding risk ratio was RR = 1.04, 95% CI [0.93, 1.16], p = .474. The E-value for the DR AIPW point estimate was 1.24, with a confidence-limit E-value of 1.00. Overall, the 2022/23 results did not provide evidence of a statistically reliable improvement in continuation associated with identification for the programme.

4.1.2. Results for the 2023/24 academic year

In 2023/24, the programme initially began using the support-services contact model from the previous year but was later paused while the approach was reviewed with faculty staff. Following consultation, the delivery model changed so that course leaders received weekly lists of disengaged students and

contacted them to explore barriers to engagement and facilitate access to support. This revised model began in mid-March 2024, meaning that delivery was interrupted for more than half of the academic year. The analytic sample included 953 students, of whom 183 were identified for the programme and 770 were in the comparison group.

Across imputations, PSM produced an average of 95.24 matched pairs, with the number of pairs ranging from 85 to 103. Matching improved overall covariate balance. Across covariates, the mean absolute SMD decreased from 0.119 before matching to 0.066 after matching. The covariate-level matched absolute SMD means ranged from 0.048 to 0.108, indicating that most covariates achieved good balance and that remaining imbalance was small on average.

The PSM estimate for 2023/24 was negative and not statistically significant. The ATT risk difference was − 3.62pp, *SE* = 5.75, 95% CI [− 14.90, 7.65], *p* = .529. The matched risk ratio was *RR* = 0.96, 95% CI [0.84, 1.09], *p* = .533. The E-value for the point estimate was 1.25. However, because the confidence interval included the null, the confidence-limit E-value was 1.00.

The DR AIPW estimate was consistent with the matched analysis. The estimated ATT risk difference was − 4.46pp, *SE* = 4.69, 95% CI [− 13.66, 4.73], *p* = .341. The corresponding risk ratio was *RR* = 0.95, 95% CI [0.85, 1.06], *p* = .345. The E-value for the point estimate was 1.29, with a confidence-limit E-value of 1.00. Therefore, the 2023/24 results did not indicate a statistically reliable improvement in continuation.

4.1.3. Results for the 2024/25 academic year

In 2024/25, the programme operated from November to the end of the academic year, using the revised course-leader contact model. This was the first full year in which course leaders received weekly lists of disengaged students and contacted them directly to offer tailored support. The analytic sample included 924 students, of whom 280 were identified for the programme and 644 were in the comparison group.

Across imputations, PSM produced an average of 180.80 matched pairs, with the number of pairs ranging from 167 to 194. Covariate balance improved after matching. Across covariates, the mean absolute SMD decreased from 0.077 before matching to 0.053 after matching. The covariate-level matched absolute SMD means ranged from 0.040 to 0.092, indicating that all covariates were, on average, below the conventional 0.10 threshold after matching. This suggests that the matched comparison group provided a well-balanced counterfactual for the identified students in 2024/25.

The PSM estimate indicated a statistically significant positive association between identification for the programme and continuation. The ATT risk difference was 10.49pp, *SE* = 3.77, 95% CI [3.10, 17.89], *p* = .005. On the risk-ratio scale, identified students were more likely to continue than matched comparison students, *RR* = 1.13, 95% CI [1.03, 1.23], *p* = .007. The PSM E-value was 1.51, suggesting that the observed association was moderately robust to unmeasured confounding. In practical terms, an unmeasured confounder would need to make participants at least 1.51 times as likely to be identified for the programme and at least 1.51 times as likely to continue in the programme to fully explain away the observed association.

The DR AIPW estimate reinforced the matched result. The estimated ATT risk difference was 12.77pp, *SE* = 3.85, 95% CI [5.21, 20.33], $p < .001$. The corresponding risk ratio was *RR* = 1.16, 95% CI [1.06, 1.28], $p = .002$. The E-value for the DR AIPW risk ratio was 1.60, indicating moderate robustness to unmeasured confounding. These findings provide convergent evidence that, in 2024/25, inclusion in the programme was associated with higher continuation among students in the overlap population.

4.1.4. Summary of quantitative results

Across the three academic years, the estimated association between programme identification and continuation varied by year. In 2022/23, when the intervention was delivered through fortnightly support-services contact, both PSM and DR AIPW estimates were positive but not statistically significant. In 2023/24, when delivery was interrupted and the model changed mid-year, both estimates were negative but again not statistically significant. In contrast, in 2024/25, the first full year of the course-leader contact model, both PSM and DR AIPW estimates indicated significantly higher continuation among students included in the programme, with adjusted differences of approximately 10 to 13 percentage points.

4.2 Qualitative strand findings

The qualitative findings reflect four interconnected themes regarding course leaders' perceptions of student continuation and the implications of the continuation programme. The themes firstly highlight descriptions of structural and course-related conditions that place student continuation at risk, which provides context for the subsequent themes which relate to roles and responsibilities for supporting students at risk of discontinuation. The third theme reflects course leaders' perceptions of how the programme's design translated into practice, including enabling features and elements requiring refinement, followed by the final theme which includes reflection on the programme's perceived contribution to continued participation, attendance, and course engagement.

4.2.1. Theme One: Perceived barriers to student continuation

4.2.1.1. Structural conditions placing continuation at risk

Course leaders understood continuation as shaped by structural conditions that constrained participation. Long commutes, travel costs, mental health difficulties, disabilities, caring responsibilities, and English as a second language could heighten vulnerability to disengagement:

"We've got students who… have like a two-hour commute every day… we're finding more and more requests to stay at home because the fuel costs so much to get them in." (CL12)

These pressures were compounded by delays in accessing disability, wellbeing or learning support, and by difficulties obtaining course materials. Risk therefore arose from students' circumstances and from barriers to timely institutional support.

4.2.1.2. Course-related concerns placing continuation at risk

Participants also identified transition difficulties, challenging placements, and unmet expectations as threats to continuation. Some students struggled with independent learning and assessment demands, while others reconsidered their course choice:

“Some of them come in not quite being ready for university or feeling like… I had to go and realised a few months in to be like, actually, I don't care about this topic...” (CL6)

Non-continuation was therefore portrayed as emerging from interacting personal, institutional, and course-related factors. Although many barriers sat outside their control, identifying risk enabled course leaders to initiate contact and connect students with appropriate support.

4.2.2. Theme Two: Shared responsibility for student continuation

4.2.2.1. The importance of course leader intervention

Course leader involvement was perceived as central to the continuation programme’s influence on student engagement. Consistent with research highlighting the value of instructor-led outreach (Espinoza & Genna, 2021), participants considered course leaders well placed to interpret risk notifications due to their student and course knowledge. This enabled them to distinguish temporary absence or administrative issues from more substantial risk to continuation:

“…I think knowledge is power… having the course leaders then being the ones to reach out, or via their personal tutors, I think is particularly useful because it’s a point of contact that probably had a bit more interaction with, and… have that deeper context of that particular student.” (CL2)

Course leaders could tailor responses by initiating contact, clarifying expectations, and directing students to relevant provision, including module tutors, placement coordinators, wellbeing support and reasonable adjustments. Notifications also strengthened local monitoring by increasing course-team awareness.

4.2.2.2 Pastoral wraparound support for continuation

Although course leaders played an important role, continuation was framed as a collective responsibility. Personal academic tutors or coaches provided relational continuity and ongoing pastoral support when utilised effectively. Sharing information with these staff allowed academic, attendance and personal difficulties to be considered together:

“What I tend to do is try and then relay that information to the personal academic coach, because obviously they are kind of the ones that are seeing them through the course… it’s good to have that awareness… I refer

them on to see if they need any support with academic work… Or is there something personally that's going on that they're not attending?" (CL8)

This wraparound approach could support earlier and more coordinated intervention, particularly after the initial four weeks. Personal tutors or coaches contributed through signposting, maintaining contact, and recognising changes in students' circumstances.

4.2.2.3. Coordination and oversight from professional services

Participants also emphasised the importance of institutional oversight, particularly on large courses. Professional services teams were understood to coordinate communications, maintain oversight of continuation activity, and clarify expected actions. Central identification, course-level interpretation, and wider support reassured course leaders that responsibility did not rest with one individual:

"…it's good to know there's someone in the background kind of picking those things up because I just can't have oversight of it, you know, every student… think it's been reassuring for me in a way." (CL8)

Effective intervention therefore depended on cross-team communication. Course-level relationships enabled personalised responses, while institutional systems provided oversight. However, shared responsibility could also create uncertainty where roles were not clearly defined. Agreed responsibilities and escalation pathways may subsequently reduce ad hoc practice and support consistent intervention with students at risk of discontinuation.

4.2.3. Theme Three: Bridging programme design and practice

4.2.3.1. Design of programme communications

Course leaders emphasised the importance of clear, regular communication in translating the continuation programme into practice. Notifications identified students at risk, clarified the programme's purpose and reassured course teams that engagement was being monitored. While some interpreted the absence of further contact as evidence that students had re-engaged, others preferred continued updates, including confirmation that no students had been identified:

"I think initially I thought there would be quite a more regular contact. I think I interpret it as like, oh, okay, we're going to keep checking in. And even if it's good news, great." (CL6)

Weekly emails therefore operated as a light-touch prompt or 'nudge', encouraging course leaders to review engagement, consider follow-up or reflect on action already taken. However, communications were perceived as valuable only when connected to relational support. The programme may therefore not be sufficient in itself, but act as a prompt for timely human intervention.

4.2.3.2. Thresholds for risk notifications

Course leaders responded positively to predictive indicators, including attendance and engagement with VLE content. Such data gave visibility of behaviours course leaders could not always monitor directly:

“It’s useful for understanding how students are engaging with the actual material on [VLE]… because that’s a metric that I… can’t check like being in the session and seeing if they’re attending.” (CL10)

Timing was also important. Identifying students during the first four weeks of the academic year enabled early and, where necessary, “more intensive work” (CL5). However, participants stressed that early engagement data required contextual interpretation. Late enrolment, limited VLE access or delays in receiving learning materials could affect whether a student appeared at risk. Timing was particularly significant in intensive delivery models, where short periods of disengagement represented a substantial proportion of teaching. Some course leaders suggested extending the capture period, including beyond first year, as later-year students may also benefit from structured monitoring, even if withdrawal is generally more common earlier in the student lifecycle (McCulloch, 2014).

4.2.3.3. Encouraging system-level approaches to prevention

The programme also supported system-level continuation by linking central oversight with local course knowledge. Participants valued professional services teams providing coordinated monitoring while involving course leaders after the initial engagement period. This enabled joined-up action:

“It’s a lot easier when you’ve got [continuation programme team] giving you… a little flag… this student hasn’t been engaging as much… it’s just helpful to have that support… and routine updates, so you can inform personal academic coaches.” (CL9)

The programme’s usefulness therefore lay in initiating collective responsibility, validating existing concerns, and reinforcing shared monitoring. Effectiveness nevertheless depended on timely, contextualised notifications and clear expectations for follow-up.

4.2.4. Theme Four: Perceived impact upon student outcomes

4.2.4.1. Enabling continued participation in study

Course leaders viewed early engagement with first-year students as critical. Course-team discussions with students about content and progression routes could enable informed decisions regarding next steps:

“… before the [continuation] program, where of course we'd try, but… it's simply harder to, you know, have oversight over it all. We would just get more withdrawals where then the reason on whatever system… would just say, you know, wrong career choice… but you've missed having that conversation with the

student before they'd done that. So that's fine if it is their decision as long as it's an informed decision. And I think the [continuation] program helps them make an informed decision." (CL3)

Such conversations enabled course leaders to reassure students, clarify expectations, signpost to services, or facilitate transfer opportunities, supporting continuous learning pathways.

4.2.4.2. Strengthening attendance and academic engagement

Course leaders also highlighted the programme's role in prompting attendance and engagement monitoring and follow-up conversations with students:

"I do remember now one student who… as a result of this communication has been trying to let us know that when she can't attend… because of… these issues. But she's still interested to stay." (CL1)

Course leaders emphasised the "positive pressure" (CL1) created by the programme. Students recognised that attendance was being monitored supportively, strengthening accountability and engagement with course content.

4.2.5. Summary of qualitative findings

Overall, continuation was shaped by intersecting structural, personal, institutional, and course-related factors. Course leaders valued the programme for identifying risk, prompting conversations, and strengthening awareness of disengagement. However, engagement data required contextual interpretation and relational follow-up. The programme also reinforced shared responsibility across course leaders, personal academic coaches, and professional services. Its value lay in enabling earlier, coordinated, relational responses that support participation, attendance, and engagement.

5. Discussion and Conclusion

This mixed-methods study investigated a LA-informed continuation programme implemented over three academic years in a UK university. The quantitative findings showed that the association between being identified for the programme and subsequent continuation rates varied substantially by year. No statistically reliable difference was observed in 2022/23 or 2023/24. In 2024/25, the first full year of the course-leader-led model, programme inclusion was associated with continuation rates approximately 10 to 13 percentage points higher than the estimated counterfactual rates. The qualitative findings help explain this pattern by highlighting that continuation work was perceived not simply as a matter of identifying risk, but as a relational, contextual, and coordinated process involving course leaders, personal academic coaches, and professional services. Taken together, the findings suggest that the value of learning analytics lies not in risk identification alone, but in how that information is translated into timely, credible, and contextually sensitive support.

5.1. When insight meets action: The importance of delivery models

A central implication of the study is that the intervention component of LA-informed continuation work requires as much attention as the predictive or identification component. Across the three years, the approach to identifying students at risk remained stable, drawing on behavioural and early academic indicators to flag students at risk of discontinuation. However, the delivery model changed substantially, from fortnightly support-services-led contact in 2022/23, to an interrupted and redesigned model in 2023/24, and then to a full-year course-leader-led model in 2024/25. This distinction is important because LA is often framed as a means of generating good insight, yet the present findings suggest that the 'action' component may be critical to whether predictive insight translates into improved outcomes (Milliron et al., 2014; Siemens, 2013).

The results therefore support the premise of 'insight and action analytics', while also qualifying it. The issue may not be whether LA can identify students who may benefit from support, but whether the subsequent intervention is delivered consistently, by appropriate staff, and in ways that students experience as meaningful. This aligns with prior evidence that LA-informed interventions can improve outcomes when combined with structured, instructor-mediated feedback, but that lighter-touch, nudge, or less relational forms of contact may produce limited effects (Dodge et al., 2015; Espinoza & Genna, 2021). In the present study, the 2022/23 support-services-led model produced small positive but non-significant estimates, while the 2023/24 interrupted model produced negative but non-significant estimates. By contrast, the 2024/25 model, in which course leaders received weekly notifications and contacted students directly throughout the academic year, was associated with a sizeable improvement in continuation.

The qualitative findings provide plausible mechanisms through which the course-leader-led model may have operated. Course leaders described continuation risk as arising from interacting structural, personal, and course-related factors, including factors such as commuting pressures, financial constraints, and uncertainty about course choice. These issues cannot be fully understood from engagement data alone. They require contextual interpretation and careful conversation. Course leaders were perceived to be well placed to interpret risk notifications because they understood course expectations, attendance patterns, assessment demands, and, in some cases, individual student circumstances. Their role enabled them to distinguish temporary disengagement from more serious continuation risk and to tailor follow-up accordingly.

5.2. Methodological contribution and causal caution

The mixed-methods design strengthens the interpretation of the findings by bringing together estimated programme associations with staff accounts of implementation and mechanism. The quantitative strand indicates that the strongest continuation outcomes coincided with the most embedded and sustained intervention model. The qualitative strand helps explain why this may have occurred,

suggesting that course leaders perceived their contact as functioning as more than a simple nudge. It created opportunities for academic and pastoral dialogue, expectation-setting, and coordination with personal academic coaches or professional services. Where students were questioning their course choice, course leaders could draw on subject-level expertise to clarify expectations, discuss progression routes, and support informed decisions about whether to continue, transfer, or access further support.

However, the quantitative estimates should be interpreted with appropriate caution. Although propensity-score matching and doubly robust AIPW estimation reduce the likelihood that findings are driven by observed baseline differences, the quasi-experimental design cannot eliminate unmeasured confounding. Differences in cohort composition, institutional context, course-level practice, staffing, or wider sector conditions may have contributed to the observed pattern of results, even though the E-values indicated moderate robustness to unmeasured confounding. The findings should therefore not be read as definitive causal proof, but as credible evidence that programme inclusion was associated with better continuation in 2024/25, when the sustained course-leader-led model was fully implemented.

The 2023/24 findings raise a further practical caution. During that year, the programme was paused and redesigned for more than half of the academic year. Although the negative estimates were not statistically significant, they are consistent with the possibility that inconsistent or interrupted delivery may limit potential benefits and contribute to missed opportunities or delayed support. This aligns with concerns in the LA literature that risk detection alone does not guarantee improved outcomes and that poorly implemented interventions can have unintended consequences (Jayaprakash et al., 2014; Summers et al., 2024). For institutions, this highlights the importance of implementation fidelity, role clarity, and continuity when designing LA-informed continuation programmes.

5.3. Limitations and directions for future research

Several limitations should be acknowledged. First, the study was conducted in a single UK university, and the findings may reflect local student characteristics, course structures, staff roles, and institutional support arrangements. Second, because the intervention model varied by academic year, it is difficult to separate the effect of delivery model from other year-level differences. Third, the quantitative analysis estimates the association between being identified for LA-informed support and continuation, rather than directly isolating the effects of specific forms of contact or student engagement with support. Finally, the qualitative strand focused on course leaders' perspectives. Student accounts are needed to understand how outreach was received, whether it felt supportive or stigmatising, and which forms of contact influenced belonging, confidence, engagement, and continuation decisions.

Future research should therefore move beyond evaluating whether LA can identify students at risk and focus more directly on which interventions work, for whom, under what conditions, and why. Comparative studies of support-services-led outreach, course-leader-led outreach, and combined models would help clarify the mechanisms through which LA-informed support produces change. Although the present study was conducted in a UK institutional context, its findings have relevance for international higher education systems facing similar challenges around student continuation. Multi-

institutional and cross-national replication would strengthen the evidence base and help determine whether course-leader-led models are effective across different regulatory environments, provider types, subject areas, and student populations.

In conclusion, this study suggests that LA-informed continuation programmes can be associated with meaningful improvements in student continuation when risk identification is paired with sustained, contextualised, and relational intervention led by course leaders. The crucial question is not whether institutions can identify at risk students, but whether they can respond in ways that change student outcomes. For universities seeking to improve continuation, the findings point towards a practical lesson that LA may generate the ‘insight’, but it is the ‘action’ that appears to determine whether the insight can lead to impact.

Declarations

Ethical Approval

The study received ethical approval from the University of Suffolk Research Ethics Committee prior to commencement (reference RETH24/065). The Committee approved the study procedures, including the proposed secondary analysis of anonymised institutional student data. All research was conducted in accordance with the University of Suffolk Research and Knowledge Exchange Ethics Governance Framework and relevant institutional research governance requirements. Access to and use of the anonymised institutional data for the approved research and evaluation purposes were additionally authorised by the University of Suffolk Data Governance Team.

Informed Consent

Informed consent was obtained from all course leaders who participated in the qualitative interviews. The quantitative strand involved secondary analysis of anonymised institutional student data and did not involve the recruitment of, contact with, or collection of data directly from students. Access to and use of these anonymised data were approved through the University's research ethics and data governance processes.

Competing Interests

The authors report there are no competing interests to declare.

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Author Contribution

CRediT Statement P.V.: Conceptualisation, Data Curation, Formal Analysis, Investigation, Methodology, Supervision, Writing – Original Draft. K.T.: Conceptualisation, Data Curation, Formal Analysis, Investigation, Methodology, Writing – Original Draft. B.H.: Data Curation, Formal Analysis, Investigation, Writing – Review and Editing. I.K.: Writing – Review and Editing.

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Data Availability

The individual-level datasets analysed in this study are not available for public or controlled-access sharing. The quantitative dataset comprises student-level institutional administrative and learning-analytics data. Access to these data was granted to the research team for the purposes of the approved study, but the authors do not hold permission from the data-owning institution to redistribute the dataset to third parties. The qualitative dataset comprises interview transcripts from course leaders. Participants provided consent on the basis that interview transcripts, including anonymised transcripts, would be accessible only to the research team. Consequently, redistribution of these data would be inconsistent with the approved ethical and consent arrangements. These restrictions apply to raw and processed individual-level data.

Materials that can be shared are provided with the article. Supplementary Material A contains the quantitative analysis code and associated analytical outputs, Supplementary Material B contains the final qualitative coding template, and Supplementary Material C contains the complete semi-structured interview schedule.

Code Availability

The complete analysis scripts used to generate the quantitative results reported in this article are provided in Supplementary Material A.

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