

STUD-U-ONAs: Behavioural Archetypes for Human-Centred Learning Analytics—A Case Study Using Microsoft Teams Insights in Education

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Abstract—Student engagement plays an essential role in academic success; however, measuring it effectively in online learning environments remains a challenge. This paper presents an action research study that applies learning analytics to behavioural engagement data collected from Microsoft Teams Insights. The study focuses on final-year undergraduate students from a computing programme and explores six behavioural indicators across multiple modules, including attendance, digital activity, and forms of communication such as posts, replies, and reactions. Using hierarchical clustering, eight learner archetypes were identified, representing patterns of engagement and academic performance. These archetypes range from consistently high achievers to students who succeed despite low observable engagement. To translate these findings into actionable insights, the study introduces STUD-U-ONAs: data-informed learner personas designed to support academics in understanding student behaviours and designing appropriate interventions. The results demonstrate the potential of combining platform-generated analytics with behavioural profiling to improve engagement monitoring and enhance teaching strategies in learning environments.

Index Terms—Student Engagement, Behavioural Learning Analytics, Microsoft Teams, Learner Archetypes, Clustering Analysis, Personalised Learning, Human-Centred Learning Analytics, STUD-U-ONAs

I. INTRODUCTION

Online learning has become an integral part of formal education, supporting both school-age learners and university students through flexible and accessible modes of instruction. Although digital platforms offer clear advantages, they have amplified long-standing challenges in understanding how students engage with learning content, peers, and instructors outside traditional classroom settings [1] [2].

The rapid adoption of platforms such as Microsoft Teams during and after the COVID-19 pandemic has changed how learning is delivered and monitored. This shift has highlighted the need to move beyond attendance and grades as the only indicators of student participation. Instead, behavioural data such as posting activity, file engagement, and meeting attendance provide more detailed insight into learning processes and offers opportunities for earlier and more effective intervention [3]. Student engagement is typically described as

a multidimensional concept, involving behavioural, emotional, and cognitive aspects. Among these, behavioural engagement, referring to the observable actions students take during the learning process, is the most readily measurable in digital environments. Analysing this type of data can help uncover learner patterns and provide early warnings for disengagement or inconsistent participation [4] [5] [6].

This study explores how behavioural data from Microsoft Teams Insights can be used to identify meaningful engagement profiles among final-year undergraduate students enrolled in a computing programme. This group was selected because they used Microsoft Teams consistently across several modules, providing a suitable dataset for investigating sustained engagement patterns in online learning.

Six engagement indicators are examined: attendance, posts, replies, reactions, file activity, and meeting participation. Using hierarchical clustering, the study identifies eight learner archetypes, each representing a unique combination of behaviour and academic outcome.

To support practical application of the findings, this paper introduces STUD-U-ONAs, a set of learner personas derived from the observed patterns. These personas are designed to help educators interpret behavioural trends and respond with personalised teaching strategies.

The study contributes to the field of behavioural learning analytics by showing how data from digital platforms can reveal patterns of engagement, presenting interpretable archetypes through clustering analysis, and offering STUD-U-ONAs as a practical framework to support academic interventions.

The remainder of the paper is structured as follows. Section II reviews related work on learning analytics and behavioural engagement. Section III outlines the research methodology. Section IV presents the findings and introduces the STUD-U-ONAs framework. Section V concludes with key implications and directions for future work.

II. RELATED WORK

In recent years, synchronous learning platforms such as Microsoft Teams, Zoom, and Google Meet have gained

widespread adoption in higher education, particularly as institutions adapted to the sudden shift to remote learning during the COVID-19 pandemic [7]. This transition has inspired a growing body of research examining how digital tools affect student engagement, interaction, and academic performance across diverse educational contexts.

Nguyen et al. [8] conducted a large-scale international study involving 4,789 undergraduate students from 95 countries. Their findings revealed a strong preference for synchronous learning over asynchronous formats, with students reporting increased motivation, social interaction, and overall satisfaction when real-time engagement was integrated into their learning experience. These results highlight the potential of synchronous platforms in promoting active participation.

Yildiz [9] analysed behavioural data from over 30,000 university students participating in synchronous online classes. By examining indicators such as camera and microphone activity on Microsoft Teams, the study identified significant performance differences across varying levels of engagement. Interestingly, students with moderate levels of interaction outperformed both low and highly interactive peers, suggesting that the quality of engagement, rather than its frequency alone, plays a crucial role in academic achievement.

Khraisat and Fakhouri [10] examined the implementation of Moodle, Microsoft Teams, and Zoom at a Jordanian university. Their mixed-methods study found that students' digital literacy, prior exposure to technology, and attitudes toward e-learning significantly influenced engagement and academic outcomes. This finding highlights the importance of learner readiness in technology-enhanced education, particularly within Middle Eastern contexts.

From a regional perspective, AlAdwani and AlFadley [11] explored Kuwaiti EFL students' perceptions of Microsoft Teams in terms of its impact on learning, interaction, and assessment. Based on survey data from 440 university students, the study reported strong correlations between interaction and both learning and assessment. These findings suggest that Microsoft Teams was perceived as a supportive tool for sustaining effective learning experiences in language-based courses during the pandemic. Given the regional proximity and similar educational settings, these insights are relevant to the our study conducted in the United Arab Emirates (UAE).

Focusing on the role of learning analytics in understanding and enhancing student engagement, Ifenthaler and Yau [12] reviewed 46 empirical studies and concluded that learning analytics interventions can help identify students at risk and support academic success. However, the authors emphasised the need for more robust, long-term evidence on the effectiveness of such tools.

Feng et al. [13] introduced a network-based approach for analysing behavioural engagement in collaborative learning settings. Their study used multimodal data to examine spatial and verbal interactions within student teams, uncovering patterns that were associated with higher levels of satisfaction and team performance. Their study points to the value of data-driven techniques in identifying individual contributions and

promoting effective collaboration.

Similarly, Zhou et al. [14] addressed the need for transparency in learning analytics by proposing an interpretable model for detecting individual engagement during face-to-face group work. Their approach allowed for the differentiation of cognitive, behavioural, and emotional engagement types, offering practical applications for real-time feedback and adaptive instruction.

Mahmud and Wong [15] investigated students' perceptions of Microsoft Teams using the Technology Acceptance Model (TAM). Their findings indicated that self-efficacy and perceived ease of use were the strongest predictors of positive experiences with the platform. This reinforces the idea that students' confidence and familiarity with technology significantly influence the success of online learning environments.

Collectively, the aforementioned studies provide important insights into how synchronous learning platforms and behavioural data analysis can enhance educational experiences. Our study contributes to this evolving discussion by focusing on behavioural engagement within Microsoft Teams in a UAE-based university. Specifically, it seeks to identify patterns of student interaction and propose an adaptive framework to support individualised learning in synchronous online settings.

Much of the existing literature centres on quantitative indicators and learning analytics; however, there is increasing recognition of the complementary value of persona-based models in enhancing the interpretability and applied relevance of engagement data. In our previous work, we conducted a survey of interaction design and user experience professionals to examine how personas are understood, created, and implemented in professional practice [16]. The findings revealed a complex landscape: practitioners recognised the value of personas in enhancing empathy, informing design decisions, and facilitating communication with stakeholders; however, they also highlighted persistent challenges, including the time and expertise required to develop personas and the inconsistency of their use across teams. These insights emphasise the need for persona development approaches that are both data-informed and contextually grounded. Building upon this earlier work, the present study extends the concept of personas into the educational domain by introducing STUD-U-ONAs, data-informed learner archetypes derived from behavioural engagement data, to support human-centred decision making and adaptive pedagogical practices.

III. METHODOLOGY

This study adopted a participatory action research (PAR) methodology to explore and understand behavioural engagement patterns among undergraduate students in a distance learning environment. Specifically, it examined how Microsoft Teams activity data could be used to profile learners' engagement through the lens of learning analytics. Conducted in the Department of Computer Engineering and Informatics at Middlesex University Dubai with Research Committee approval, the study ensured compliance with UK data protection laws. Data were securely stored on encrypted servers, and student

identifiers were replaced with anonymised personas to preserve trends while preventing re-identification.

A. Research Design and Motivation

The motivation behind the study was twofold: first, to investigate whether digital engagement indicators could reveal meaningful behavioural patterns; and second, to inform data-driven pedagogical strategies that support learners' academic progression. The research questions focused on identifying commonalities in student interaction, understanding cross-module behavioural consistency, and exploring correlations with academic achievement.

Our primary goal was to evaluate whether engagement patterns could be clustered into behavioural archetypes, which would in turn support proactive teaching and mentoring. The study embraced an action-oriented design to not only investigate but also implement change within the teaching process.

B. Sample and Context

The sample consisted of final-year undergraduate students from the CEI programmes, specifically those studying Business Information Systems and Information Technology. These students were selected based on their enrolment in common optional modules. This cohort was considered appropriate for the study due to their shared curriculum exposure and the availability of rich engagement data across multiple modules.

1) *Participants:* The study analysed data from 27 final-year undergraduate students. The cohort included 16 BIS students (59%) and 11 IT students (41%). The participants were aged between 19 and 24 years. The group included 21 male (78%) and 6 female students (22%). In terms of nationality, the students were primarily from Nigeria, Pakistan, and India, with 12 students from Nigeria (44%), 9 from Pakistan (33%), 4 from India (15%), and one from Iran (4%). All participants engaged with learning activities delivered through Microsoft Teams over the academic year, making them suitable for examining patterns of digital behavioural engagement.

C. Data Collection and Preprocessing

Behavioural engagement data were collected from Microsoft Teams Insights, covering a full academic year (24 weeks). The indicators were aggregated across the 24-week period for each module, except for enrolment status, which is a static attribute. Academic Performance was calculated at the end of the 24 weeks (or after resits). The indicators include:

- 1) Attendance (Module-Attendance-Percent, Module-Attendance-Freq): -Percent = share of sessions attended; -Freq = number of sessions. Multiple check-ins per session counted once.
- 2) Digital Engagement (Module-Digital Activity-Percent, Module-Digital Activity-Freq, Module-Posts, Module-Replies, Module-Reactions): Captures online actions in MS Teams. -Percent = activity relative to peers; -Freq = raw count of logins, clicks, and contributions. Includes posts (new threads), replies (responses), and reactions (emoji

acknowledgements). Rapid duplicates, repeated replies, and multiple reactions were collapsed/deduplicated.

- 3) Enrolment Status: 1 = direct-entry, 0 = standard pathway.
- 4) Academic Performance (Module-Academic Performance): Initial and, where applicable, resit score (resit replaces original). Scale: 1 = highest grade, 16 = pass, 17–19 = fail, 20 = failure.

After cleaning the dataset by removing inconsistencies, outliers, and incomplete records, followed by normalisation, the resulting matrix contained behavioural traces for each student across all modules. This enabled comparative analysis both within and across modules and academic years.

Table I shows engagement varied by module, with attendance highest in CST3180 (76.5%) and lowest in CST3990 (58.9%), while digital activity peaked in CST3310 (27.2%) and dipped in CST3340 (18.4%). These differences underpin the clustering analysis.

D. Data Analysis

A combination of exploratory data analysis and cluster analysis was employed to identify engagement typologies. The focus was placed on interpreting behavioural signals rather than raw performance data alone.

1) *Clustering Procedure:* Hierarchical clustering with Ward's linkage [17] and Euclidean distance was employed, as this method minimises within-cluster variance and yields compact, interpretable groups. For reproducibility, dendrograms were consistently cut at height = 120 for each of the four modules. To aid interpretation, two complementary visualisations were applied: (a) a hierarchical heatmap (Figure 1) of normalised engagement metrics (attendance, posts, replies, reactions, academic performance), where darker shades denote higher activity; and (b) a hierarchical dendrogram (Figure 2, where merge height reflects dissimilarity. Cutting at height 120 yielded clear behavioural clusters forming the statistical baseline for later refinement.

2) *Validation:* Cluster validity was assessed using silhouette score (cluster compactness/separation) and cophenetic correlation coefficient (CCC, fidelity of dendrogram structure). CST3180 achieved a silhouette of 0.39 and CCC of 0.86, indicating moderate separation and reliable fidelity. CST3340 scored higher (0.44, 0.91), while CST3310 achieved the strongest validity (0.47, 0.92). In contrast, CST3990 collapsed into a single cluster at the cut height, precluding silhouette calculation.

3) *Dendrogram Cut Height:* At the chosen cut height, CST3180 yielded four clusters: (H1) Predictable Low Achievers with low attendance (43%), modest digital engagement, and near-pass performance (~12.8); (H2) Mixed Achievers (Core) with high attendance (83%), moderate online activity, and mid-range performance (~9.0); (H3) Outlier High-Activity Achievers with intense forum activity but moderate grades (~8.5); and (H4) Unpredictable Strugglers combining high attendance (94%) with digital engagement but weak grades (~6.0). Similarly, CST3340 produced three clusters, distinguishing Unpredictable Strugglers (very high replies, weaker

TABLE I: Descriptive Statistics of Attendance and Digital Activity Metrics Across Modules

Module Code	Module Name	Metric	Mean	Std Dev	Min	Median	Max
CST3180	UX in Design	Attendance_Percent	76.5	19.7	17.0	83.0	96.0
CST3310	Strategic Information Systems (Enterprise Project) Management	Digital Activity_Percent	27.2	9.5	6.0	26.0	42.0
CST3340	Business Intelligence	Digital Activity_Percent	18.4	6.5	4.0	17.0	32.0
CST3990	Individual Project	Attendance_Percent	58.9	15.3	30.0	60.0	90.0

performance ~ 5.2), Predictable Achievers with low attendance and modest outcomes (~ 10.5), and Consistent Achievers with strong attendance (86%) and average outcomes (~ 5.5). CST3310 formed three groups: Predictable High Achievers (very high replies, performance ~ 3.8), Unpredictable Achievers (low attendance, moderate grades ~ 6.0), and Consistent Achievers (82% attendance, ~ 6.3 performance).

4) *Manual Refinement*: Ward’s clusters, though statistically valid, often merged distinct subtypes. To improve interpretability, clusters were refined through feedback from teaching staff and academic support units, ensuring contextual and pedagogical relevance. For example, in CST3180, statistical groups were mapped into archetypes, such as distinguishing an Unpredictable Free Rider from the broader low-achiever category. This process ensured that statistical patterns yielded meaningful teaching insights.

5) *Engagement Archetypes (STUD-U-ONAs)*: Figure 3 and Figure 4), termed Student User Online Navigation Archetypes (STUD-U-ONAs), which reflected both predictable and unpredictable patterns of achievement and engagement. These archetypes were:

- 1) Predictable High Achiever
- 2) Unpredictable Grade Struggler
- 3) Predictable Achiever
- 4) Predictable Low Achiever
- 5) Unpredictable Low Achiever
- 6) Unpredictable High Achiever
- 7) Unpredictable Free Rider
- 8) Predictable Failure

E. Action Plan and Implementation

We developed an action plan informed by the aforementioned engagement archetypes to facilitate early intervention, targeted mentoring, and teaching strategies. Insights from student personas enabled educators to refine formative assessment practices, provide personalised career guidance, and offer additional academic support to learners identified as at risk.

This human-centric analytics approach shifted the emphasis from passive monitoring to meaningful, ethically grounded engagement. It allowed educators not only to recognise patterns of student behaviour in online environments but also to implement timely, pedagogically aligned interventions.

IV. RESULTS AND DISCUSSION

This study applied Learning Analytics to behavioural engagement data collected via Microsoft Teams Insights for a

group of final year undergraduate students. The purpose was to classify students into learner archetypes based on digital behaviours across four modules and explore the relationship between these behaviours and academic performance. Hierarchical clustering revealed eight learner archetypes, provided in Section III (D). These archetypes emerged from behavioural indicators including attendance, digital activity, posts, replies, and reactions.

The analysis revealed notable patterns within and across modules. Firstly, certain students consistently demonstrated high levels of digital engagement (e.g. attendance, interaction through posts and reactions); however, this did not always correlate with higher academic performance. The "Unpredictable Grade Struggler" group, which constituted 18% of the students, shows this discrepancy. These students exhibited strong digital participation but did not achieve top grades. This suggests that while digital engagement is necessary, it is not a sufficient condition for academic success. Cognitive or affective factors, not directly measurable through behavioural analytics, may influence their outcomes.

In contrast, the "Unpredictable Free Rider" (7% of the sample) defied expectations by demonstrating minimal digital engagement while still achieving pass grades. This anomaly raises questions about academic integrity and assessment design. These students may be utilising prior knowledge, external support, or selective participation to succeed. Their presence in the dataset highlights the importance of triangulating behavioural data with other indicators, including one-on-one assessments or interviews, to better understand underlying behaviours and motivations.

Another significant finding was that a student’s behavioural engagement profile tended to remain stable across modules. However, their academic outcomes varied, leading to instances where students belonged to different archetypes when analysed at the module level versus across the academic year. This observation supports the need for continuous and holistic monitoring rather than static classifications. Behaviourally consistent students may still require personalised academic interventions, depending on module-specific challenges.

Moreover, these archetypes offer educators a lens through which to personalise academic support and adjust teaching strategies. However, for these insights to translate into practice, they must be made accessible and relatable to teaching staff. Therefore, our study introduced STUD-U-ONAs: visual and human centric representations of each archetype. These aim to bridge the gap between data analytics and educa-

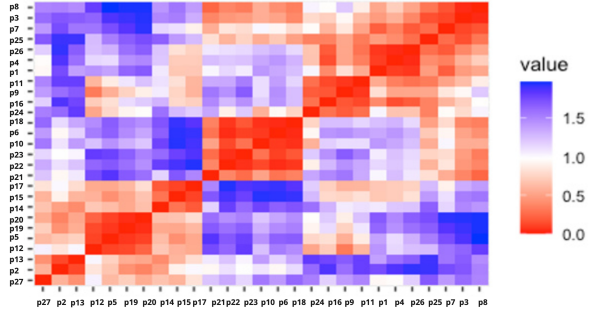


Fig. 1: Clustered Heatmap of Normalised Student Engagement Metrics Across Modules

tor interpretation. These fictionalised personas consolidate behavioural summaries, academic performance, and tailored intervention strategies. For instance, Sami (Figure 3) represents a Predictable Low Achiever with minimal digital engagement but contentment with a pass grade, while Fulla (Figure 4) represents an Unpredictable Grade Struggler who is highly active online but underperforms academically. These personas are designed to enhance understanding and support by making complex data patterns relatable to educators.

These results validate the usefulness of learning analytics for categorising student behaviours, but they also reveal the complexity of engagement. Behavioural data alone cannot fully capture the intricacies of student learning. Therefore, integrating learning analytics with qualitative feedback and broader contextual factors such as socio-economic background or psychological well-being is vital.

Furthermore, this research highlights the potential of behavioural archetypes in informing proactive academic advising, curriculum design, and institutional policy. When early warning signs are identified and personalised support is aligned to specific learner profiles, universities can support more inclusive and effective learning environments. The concept of STUD-U-ONAs may also support peer mentoring, student reflection, and career guidance.

Our results suggest that behavioural engagement is an essential component of student success; however, it must be analysed in conjunction with other data sources. The proposed archetypes and STUD-U-ONAs framework contribute a replicable and scalable model for behavioural learning analytics that aligns with action research principles and supports ethical, learner-aware design in education.

However, this study has limitations. It focused on a single cohort, limiting generalisability across contexts. The analysis relied mainly on MS Teams metrics, which may not reflect the full spectrum of student behaviour. Moreover, the absence of emotional and cognitive engagement data—such as motivation, self-regulation, and resilience—left key dimensions unexplored. A follow-up study will extend the analysis to multiple cohorts and programmes for greater robustness and will integrate additional sources such as surveys, reflective journals, and potentially biometric or sensor data to capture emotional and

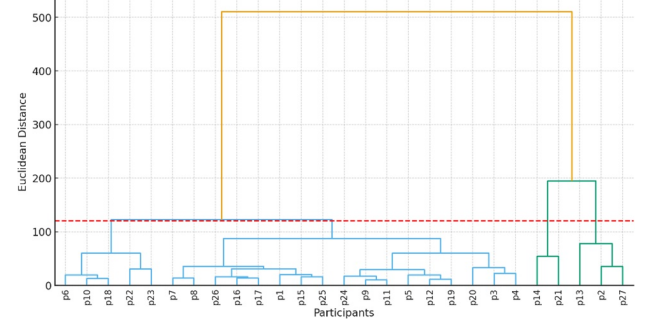


Fig. 2: Hierarchical Clustering Dendrogram of Student Engagement Patterns in Module (CST3180)

cognitive aspects of engagement. To complement behavioural metrics, future iterations of this action research will also include qualitative methods—such as student interviews, surveys on cognitive and emotional states, and educator focus groups—to provide richer insights into learner motivations, challenges, and strategies, particularly for the “Unpredictable” archetypes. Furthermore, research will explore more sophisticated measures of digital engagement quality within MS Teams, including natural language processing of posts and replies, sentiment analysis, and examination of collaborative activities such as shared document editing. By expanding data sources, incorporating qualitative insights, and refining digital engagement analysis, the next phase of this research aims to provide a more holistic, ethically grounded, and replicable model of student engagement, while strengthening the STUD-U-ONAs framework as a practical tool for learning analytics and advising. Finally, the research will test how STUD-U-ONAs can be embedded into early warning systems and academic advising processes, with pilot trials to assess their value in enhancing student support, retention, and success.

V. CONCLUSION

This study used Microsoft Teams Insights to analyse attendance, digital activity, posts, replies, and reactions across four modules, identifying eight learner archetypes. These profiles revealed that engagement patterns did not always align with performance: some highly active students underperformed, while others with minimal engagement still passed. The findings highlight the need for nuanced interpretations of engagement beyond surface-level metrics.

The introduction of STUD-U-ONAs, a human-centred representation of each archetype, was a major contribution of this research. We offered a narrative and visual identity to each learner group; the framework made the data more relatable and actionable for teaching staff. These personas bridged the gap between technical insights and practical pedagogy, supporting early intervention, mentoring, and adaptive teaching responses.

Furthermore, the consistency of behavioural patterns across modules, despite fluctuations in grades, emphasised the value of continuous and context-aware monitoring. The findings reinforced that behavioural data is valuable, but should be

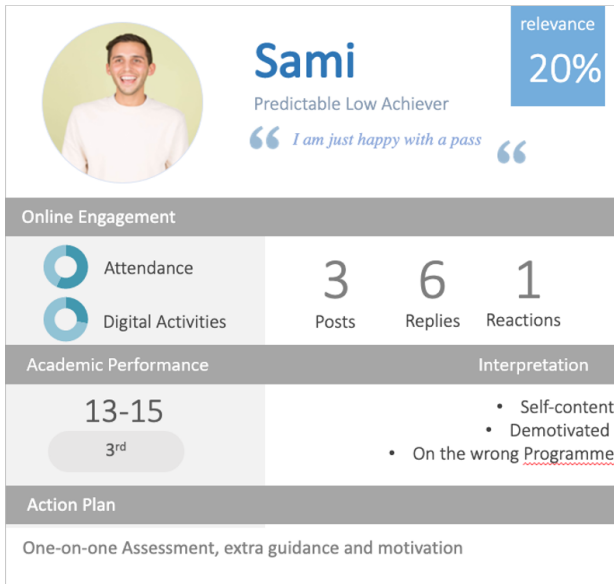


Fig. 3: Predictable Low Achiever STUD-U-ONA

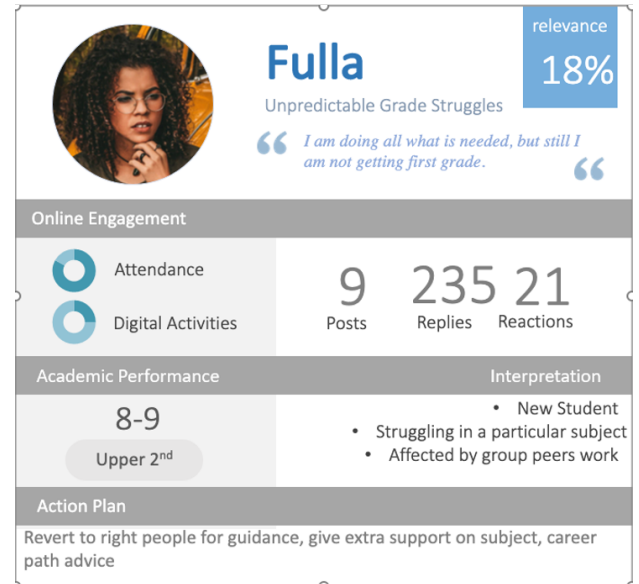


Fig. 4: Unpredictable Grade Struggler STUD-U-ONA

triangulated with other information such as personal circumstances, cognitive abilities, and emotional wellbeing to inform truly inclusive and responsive academic support.

Our research contributes a practical, replicable model for using learning analytics to enhance student support. It supports educators in moving from passive observation to informed action, helping institutions to build more inclusive and effective digital learning environments.

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