The International Journal of Engineering and Science (IJES)
|| Volume || 14 || Issue 11 || November || Pages || PP 36-39 || 2025 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Key Behavioural Indicators of Low Academic Performance in Online Units

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Abstract
Online education has expanded access to higher education, but performance in online mandatory units remains a persistent problem. The research synthesizes existing empirical studies to determine the key behavioural predictors of poor academic performance in online units. Infrequent logins, decreased time spent studying learning resources, low levels of forum participation, and lack of regular submission of assignments are identified as strong predictors of poor performance. These behaviour markers are a foundation for early warning systems, pedagogical change, and institutional policy development. By locating findings in Open, Distance, and e-Learning (ODeL) environments, the research accentuates the imperative of pairing behavioural analytics with supportive interventions to enhance student retention and academic performance.
Keywords: *Online learning; Behavioural indicators; Low academic performance; ODeL; Learning management systems; Student engagement*

Date of Submission: 01-11-2025 | Date of acceptance: 10-11-2025

I. INTRODUCTION

The abrupt shift to e-learning has redirected higher education, with flexibility and accessibility offered by platforms such as Moodle and Blackboard. Nonetheless, these benefits, universities still face difficulties in ensuring student performance, particularly in required online common units where the students are pooled from diverse academic backgrounds (Huang et al., 2020). Unlike traditional face-to-face classrooms, online learning relies on traces of student activity in the virtual setting. Patterns such as frequent login per week, usage of resources in terms of time, active participation in forums, and pattern of assignment submission are used to be good predictors of performance and persistence (Macfadyen & Dawson, 2010). But institutions only make use of such information at large, only detecting poor performance when grades are finally released (Siemens & Long, 2011). It is necessary to find out behavioural low-performance predictors so that supportive systems may be established beforehand. Research proves that intermittent logon patterns, late and incomplete assignments, and low frequency of postings in the forum are likely to follow poor academic performance (You, 2016). In working with such trends, universities are able to run early intervention to prevent disengagement and ensure retention. Unique behavioural patterns such as intermittent logins, low interaction with learning content, low participation in forums, and infrequent submission of assignments inexorably lead to poor academic performance in online courses, and an understanding of such patterns is essential for student monitoring development, informing institutional policy, and guiding future research in online education.

Background and Context

This has provided avenues for flexible, inclusive learning, particularly through Learning Management Systems (LMS). Despite such advancements, academic underachievement in online common units is widespread, threatening student progress and institutional performance. In ODeL settings, students are likely to move across diverse socio-economic and infrastructural hurdles, making it difficult to track academic risk. Conventional performance metrics, e.g., end-of-course grades, are inadequate for effective timely intervention. By contrast, behavioural statistics from LMS sites provide instantaneous insights into engagement. This article places its discussion within this larger context, highlighting the imperative to operationalize the behavioural measures into institutional support initiatives.

II. METHODOLOGY

The research employs the qualitative review method, drawing on peer-reviewed empirical studies in the learning analytics and online learning field. The sources came from existing studies that have been conducted on predictors of academic success in behavioural settings, with emphasis on LMS-based studies. Indications worth considering are login patterns, learning resource time usage, forum activity, and assignment submission patterns. Analysis brings these observations together in a consideration of the implications for ODeL institutions.

Theoretical Framework

The study relies on Learning Analytics and Self-Regulated Learning (SRL) theory. Learning analytics provides the methodological foundation for behavioural traces extraction and interpretation from digital learning spaces in an effort to forecast student performance (Siemens & Long, 2011). SRL theory explains how behaviours such as frequent logins, timely submissions, and collaborative engagement reflect self-management and metacognitive techniques required to thrive with online learning (Zimmerman, 2002). These models validate the focus on behavioural tendencies as essential determinants of academic achievement in online environments.

III. LITERATURE REVIEW

Researches on web-based learning are repeatedly supplementing the robust association between student behaviour in web-based environments and performance. Learning Management Systems (LMS) make precise records of student behaviour, and this yields measurable indicators in the form of login rate, content spend, forum participation rate, and submission pattern for assignments. These behaviour patterns give good surrogates for persistence and engagement, both being central to forecasting academic success or failure (Macfadyen & Dawson, 2010).

The most powerful of the behavioural measures is login intensity. Frequent loggers in the course are anticipated to remain active in the course, catch up on materials in due time, and meet submission deadlines. Seldom or sporadic logins are typical for disengagement and have been linked with low performance (You, 2016). The same pattern can be observed in how much time a student spends accessing learning resources. Though excessive interaction does not always translate into profound learning, inadequate or inconsistent access to course content is frequently associated with lower grades, especially in large online courses where self-directed learning is inevitable (Gašević et al., 2015).

Discussion forums participation is another very effective academic performance indicator. Online learning environments will generally rely on peer discussion and collaborative learning to substitute for face-to-face communication. Engaged student contributors in forums exhibit heightened motivational and cognitive involvement, while passive students are more likely to get poor grades (You, 2016). Xing and Du (2019) recognized declining forum activity over the course of the semester as an early warning sign for students that could be at risk of failing, emphasizing the temporal aspect of engagement metrics.

Patterns of submissions on assignments are no less significant. Timely submissions show responsibility and academic discipline, while skipped or late assignments always are accompanied by low grades. In their online learning study, Zhao and Bilen (2021) illustrated that submission trends were among the strongest predictors of academic risk, particularly when combined with other warning signs such as login anomaly. This finding is supported by Macfadyen and Dawson's (2010) research, which underscored the significance of submission patterns in early intervention system development.

Even as these indicators are invariably authenticated by literature, context-specific challenges complicate their interpretation. Limits in infrastructure and socio-economic conditions in the majority of developing countries impact the behaviour of students on internet websites. For instance, poor access to the internet or low digital literacy can lead to absent logins or inability to deliver deadlines, not necessarily disengagement but due to external limitations (Makokha & Mutisya, 2016). Lee and Choi (2011) further argue that behavioural data cannot clearly account for academic performance in the absence of learner preparedness and organizational support systems. Nonetheless, even with these constraints, behavioural metrics remain unable to be rid of the responsibility of providing scalable and real-time feedback on student performance.

Machine learning in education has also expanded research on behavioural metrics. Supervised models like logistic regression, decision trees, and random forests have been applied increasingly to LMS data to grade students based on the risk level. Aljohani (2016) demonstrated that decision tree models were effective at forecasting dropout risk based on behavioural metrics such as log-in frequency and forum use. Zhao and Bilen (2021) also found that ensemble models including random forests consistently produced strong results when analysing diverse behavioural data. These studies highlight the growing capability of predictive analytics to go beyond descriptive analysis for proactive academic intervention.

There are, however, several areas that are still lacking. Much of the existing research is performed in Asian or Western environments with better-developed online learning spaces. As a result, the African university-specific problems remain insufficiently represented, leading to uncertainty around the applicability of predictive models in them (Ng'ambi et al., 2016). Furthermore, while behavioural data can create valuable signals, they are scarcely integrated with real-time institutional operations. The studies level off at model development, rather than operationalize knowledge in early warning systems integrated into LMS environments (Pardo & Siemens, 2014). Ethical issues also need to be explored because applying behavioural data has the potential to undermine privacy, consent, and actually stigmatise low-achieving students on the basis of anticipated performance (Slade & Prinsloo, 2013).

IV. DISCUSSION

Literature reviews conclusively show that student behaviour in online classrooms yields revealing indicators of success in the academic space. Across a number of contexts, login patterns, time spent on learning content, forum activity engagement, and patterns of assignment submission all consistently emerge as indicators of academic risk. These indicators are conventional but, in situations of Open, Distance, and e-Learning (ODeL) contexts where learner autonomy and institutional offerings are highly uneven, need to be assessed with a high degree of caution.

Login frequency is perhaps the most immediate measure of behaviour. Infrequent login into the LMS by such students makes them lose interest in the learning process and miss crucial content and deadlines. This is most problematic for obligatory common units, where the students are already likely to feel that the content is peripheral to their program of study. An erratic login pattern undermines engagement with course materials and represents poor time management and self-regulation, two of the success determiners in online learning environments (Macfadyen & Dawson, 2010; You, 2016).

Time spent engaging with learning resources is a more nuanced scenario. While prolonged contact with resources was found to be an indication of active learning, limited usage can reflect indifference or barriers to access. Conversely, extended time online does not necessarily translate into effective learning since some learners might spend long periods online, but they do this passively without actually engaging with content (Gašević et al., 2015). For this purpose, time-based metrics are best understood when they are examined alongside other behaviours like activity on forums and submissions.

Forum participation is a significant factor because it indexes collaborative learning, which is harder to get in online settings. Active forum participation signifies motivation and higher investment in course materials, while forum silence can signify isolation, lack of confidence, or disengagement. Xing and Du (2019) emphasized the predictive power of declining forum participation, adding that students tend to disengage gradually and not abruptly. This makes forums especially effective for detecting early indicators of performance risk.

Assignment submission tendencies are probably the strongest indicator of poor academic performance. Late or missed submissions more strongly suggest academic difficulty than other behaviours. Zhao and Bilen (2021) demonstrated that submission metrics were some of the strongest predictors of academic success, especially when combined with login and forum participation. Since assignments typically represent a considerable portion of final grades, submission tendencies have predictive and diagnostic utility in the context of understanding student attainment.

While such signals are actionable, interpretation is context-dependent. In a third-world setting, students are likely to face structural issues such as partial internet connectivity and the lack of digital tools, which can mirror signals of disengagement (Makokha & Mutisya, 2016). A student may fail to log in due to capricious connectivity rather than lack of interest. Similarly, reduced use of forums could be due to lack of digital literacy rather than academic disengagement. Thus, while useful, behavioural indicators must be placed in the context of broader socio-economic and institutional trends (Lee & Choi, 2011).

The integration of machine learning offers a promising way to render such indicators more credible. By examining patterns in a number of behavioural variables, predictive models can remove noise and identify vulnerable students more accurately (Aljohani, 2016; Zhao & Bilen, 2021). But as the literature cautions, predictive systems are often not implemented. Universities build models but fail to follow through with implementing them as functional early warning systems that alert instructors and advisors (Pardo & Siemens, 2014). Implementing predictive models in LMS systems for common units offered online can help with creating timely alerts so instructors can intervene before grades drop.

V. IMPLICATIONS

The identification of low academic achievement behavioural markers has significant implications for teaching staff and institutions. Initially, these markers are the beginning point for early warning systems that can alert instructors to intervene when students are at risk. For example, fluctuating logins and failed submissions could be automatically utilized to trigger interventions such as personalized feedback, reminders, or referrals to learning assistance services. In this way, institutions are redirected from reactive measures that only intervene after students have failed.

Additionally, learning behaviour can guide pedagogical adjustments. When discussion activity remains consistently low within a common unit, instructors will have to restructure discussion activity to encourage more active participation. Similarly, patterns of low use of course materials can locate the necessity for more formal instructional planning or more convenient materials. Also, behavioural indicators are helpful for policy and planning. By identifying those units or courses with the highest disengagement rates, administrators may direct faculty training, invest in virtual infrastructure, or introduce student support initiatives. Ethical issues, nevertheless, as numerous studies note, remain the top priority. The use of data must respect students' privacy, avoid stigmatization, and ensure interventions to be helpful rather than punitive (Slade & Prinsloo, 2013).

VI. CONCLUSION

Behavioural indicators such as frequency of login, use time on resources, forum participation, and assignment submission patterns are commonly linked with poor academic achievement in online courses. Contextual factors complicate interpretation, but these measures provide a solid basis for early intervention. With the application of learning analytics and machine learning, institutions are able to move toward predictive support systems that maximize collective unit performance. The strategic use of behavioural data offers a door to more responsive, equitable, and student-centred online learning.

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