

# Digital Learning Behaviour and Academic Performance: Evidence from Moodle Log Analysis at the Faculty of Management and Commerce, South Eastern University of Sri Lanka

AJM Hasmy<sup>1</sup>, MBM Irshad<sup>2</sup>

<sup>1,2</sup>Faculty of Management and Commerce, South Eastern University of Sri Lanka

hasmie@seu.ac.lk<sup>1</sup>, mbmirshad@seu.ac.lk<sup>2</sup>

**Abstract:** The rapid expansion of e-learning platforms in South Asian higher education institutions has generated large volumes of student interaction data that remain largely underutilised for improving pedagogical outcomes. This study investigates the relationship between student digital behaviour—as captured through Moodle Learning Management System (LMS) log data—and academic performance at the Faculty of Management and Commerce, South Eastern University of Sri Lanka (SEUSL). Drawing on activity log records from 89 undergraduate students enrolled in the Computer Applications for Accounting (ACM 31043) course during the 2023/2024 academic year, this research employs Pearson correlation analysis, independent-samples t-tests, and Random Forest classification to identify predictors of academic success. Key findings reveal that file access frequency and quiz attempt rates are statistically significant positive predictors of final grade ( $r = 0.38, p < 0.05$ ;  $r = 0.44, p < 0.05$  respectively). Female students ( $n = 66$ ) demonstrated notably higher engagement levels and superior academic outcomes compared to their male counterparts ( $n = 23$ ). Temporal analysis confirms that student activity peaks sharply on the day preceding mid-term and final examinations, consistent with last-minute study behaviour. The study concludes with evidence-based recommendations for early academic intervention, personalised learning design, and the strategic deployment of Moodle analytics plugins to support at-risk student identification in Sri Lankan higher education contexts.

**Keywords:** Learning Management System, Moodle, Learning Analytics, Student Behaviour, Academic Performance, Higher Education, Sri Lanka

## 1 Introduction

The globalisation of higher education, combined with the widespread adoption of digital technologies, has fundamentally transformed how teaching and learning are organised in universities across the developing world. In Sri Lanka, higher education institutions have increasingly integrated e-learning tools into their curricula, driven by national digitalisation policies and the pedagogical disruptions caused by the COVID-19 pandemic (University Grants Commission [UGC], 2022). Among the digital platforms adopted, the Moodle Learning Management System (LMS) has emerged as the most prominent, offering a robust ecosystem of tools for content delivery, assessment, communication, and student tracking.

Despite widespread adoption, relatively few studies have examined how student interactions within Moodle translate into measurable academic outcomes in the context of South Asian business education programmes [2]. This gap is particularly significant because student engagement patterns in management and commerce faculties may differ substantially from those documented in engineering or computer science contexts, which dominate the existing learning analytics literature [3].

Learning Analytics (LA) has emerged as a scientific discipline concerned with the measurement, collection, analysis, and reporting of data about learners and their contexts, with the explicit purpose of understanding and optimising learning and the environments in which it occurs [4]. Moodle's native logging functionality records every student interaction with the platform, generating timestamped, IP-tagged event records that form the empirical basis for LA research. The aggregation and statistical analysis of these records can reveal patterns in study behaviour, identify academically at-risk students, and inform data-driven curriculum redesign decisions [5].

At the Faculty of Management and Commerce, SEUSL, Moodle has been employed to support blended learning across all undergraduate programmes since 2019. Despite the accumulation of several academic years' worth of log data, these records have not previously been subjected to systematic analysis. The present study addresses this gap by analysing log files from the 2023/2024 academic year for the Computer Applications for Accounting (ACM 31043) course, with two overarching research questions:

**RQ1:** To what extent do individual variables derived from Moodle log data constitute reliable predictors of academic success among management and commerce students at SEUSL?

**RQ2:** What gender-based differences exist in Moodle engagement patterns and associated academic outcomes?

The remainder of this article is structured as follows: Section 2 reviews the Moodle LMS and its learning analytics plugins; Section 3 presents the related literature; Section 4 describes the research methodology and data analysis procedures; Section 5 reports and discusses the empirical findings; and Section 6 offers conclusions and recommendations for future research and practice.

## 2 The Moodle LMS and Learning Analytics Plugins

Moodle (Modular Object-Oriented Dynamic Learning Environment) is an open-source LMS maintained by a global developer community and used by over 300 million users across 242 countries as of 2024 [6]. Its architecture is modular, built around a core set of plugins that can be extended, customised, and supplemented with third-party contributions. Core plugins relevant to standard teaching activities at SEUSL include Assignment, Quiz, Forum, Resource, Attendance, Feedback, and SCORM Package [6].

In addition to its pedagogical tools, Moodle offers a growing suite of plugins specifically oriented to learning analytics. Table 1 summarises the most relevant LA-oriented plugins evaluated for use in this study, categorised by their primary analytical function.

**Table 1** Summary of Key Moodle Learning Analytics Plugins

Plugin	Key Feature	LA Category
Inspire Analytics	At-risk student prediction	Predictive Analytics
SmartKlass™	Student lagging detection	Descriptive Analytics
Engagement Analytics	Engagement scoring	Descriptive Analytics
Course Dedication	Time-on-task estimation	Descriptive Analytics
Heatmap	Visual activity mapping	Visual Analytics
Configurable Reports	Custom SQL-based reports	Ad-hoc Analytics

*Note.* Compiled from Moodle HQ (2024) and plugin documentation.

Among these plugins, Inspire Analytics (now integrated as the core Analytics framework in Moodle 3.8+) is particularly noteworthy for its predictive model that identifies students at risk of course non-completion based on low engagement indicators [7]. The SmartKlass™ plugin complements this by identifying both underperforming and insufficiently challenged students, allowing differentiated pedagogical interventions [8]. For the purposes of this study, however, raw log file extraction and offline statistical analysis were employed, ensuring methodological transparency and reproducibility.

A Moodle log entry records: a Unix timestamp, the IP address of the accessing device, the full name of the student, the context (course, module, activity), the event component (e.g., mod\_quiz, mod\_forum, mod\_resource), the action type (viewed, submitted, updated, deleted), and the target object [6]. These fields collectively enable reconstruction of complete learning session timelines for each enrolled student.

### 3 Related Work

Research on learning analytics and student behaviour in LMS environments has grown substantially over the past decade, with a noticeable shift toward predictive modelling and machine learning approaches in more recent work.

#### 3.1 Engagement and Academic Performance

Tlili et al. (2021) conducted a systematic review of 87 empirical LA studies and found that LMS engagement metrics—particularly content access frequency, time-on-task, and formative assessment completion rates—consistently predicted summative academic performance across diverse disciplinary contexts. Their meta-analysis reported an average correlation of  $r = 0.42$  between overall LMS activity volume and final course grade, with the strongest associations found in courses with high proportions of online formative assessment.

Herodotou et al. (2020) examined the impact of LA-driven dashboards on student self-regulation at the UK Open University, finding that students who received real-time feedback on their engagement relative to class averages improved their final module scores by an average of 5.3 percentage points. This finding highlights the dual role of log analysis: not only as a research tool but as a direct pedagogical intervention mechanism.

Lara et al. (2022) applied a temporal network analysis approach to Moodle logs from a Colombian business school, demonstrating that the sequence of student activities—rather than the raw frequency of individual actions—was a more powerful predictor of grade outcomes. Students who accessed forum discussions before attempting quizzes showed significantly higher performance than those who reversed this order, suggesting the importance of peer-mediated sense-making prior to formal assessment.

#### 3.2 Predictive Modelling of Academic Outcomes

Machine learning approaches to student performance prediction using LMS data have proliferated since 2018, with ensemble methods and deep learning architectures demonstrating the strongest predictive validity. Waheed et al. (2020) applied a deep neural network to Moodle log data from a Pakistani university, achieving a prediction accuracy of 87.3% for identifying at-risk students at the midpoint of the semester. Features engineered from raw logs—including session length variance, inter-session interval, and the ratio of resource views to assignment submissions—proved more informative than raw activity counts.

Alamri et al. (2021) compared six classification algorithms (Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, Naïve Bayes, and k-Nearest Neighbour) for predicting student final grades using Moodle engagement features. Random Forest achieved the highest AUC (0.89) and accuracy (84.1%), with quiz attempt frequency and file download count emerging as the two most important predictive features. These findings directly informed the choice of Random Forest as the primary classifier in the present study.

In a South Asian context specifically, Jayawardena and Perera (2021) analysed Moodle logs from a Sri Lankan state university and found that early-semester engagement (measured in the first four weeks) was a significantly stronger predictor of final performance than mid-semester engagement, highlighting the potential for early intervention programmes based on LA signals.

#### 3.3 Gender Differences in LMS Engagement

Gender-based differences in LMS engagement have been documented across multiple national contexts, though the direction and magnitude of effects vary considerably. Hmedna et al. (2020) found that female students in a Moroccan e-learning context submitted assignments significantly earlier, accessed resources more frequently, and achieved higher grades than male counterparts. Consistently, analysis by Nguyen et al. (2021) across Vietnamese

higher education institutions confirmed that female students' greater reflective engagement with discussion forums partially mediated the gender–grade relationship.

In contrast, Aljohani et al. (2019) reported no statistically significant gender differences in overall LMS activity volume at a Saudi Arabian university, though females showed qualitatively different engagement patterns, favouring asynchronous resources over synchronous tools. These contrasting findings underscore the contextual sensitivity of gender effects in LA research and motivate the inclusion of gender as an analytical variable in the present study.

### **3.4 Temporal Patterns of Student Activity**

Procrastinatory behaviour—characterised by sharp spikes in LMS activity immediately preceding assessments—has been documented consistently in the LA literature. Chen and Jang (2022) identified three distinct temporal engagement profiles in a Taiwanese online MBA programme: Consistent Engagers (23% of students), Pre-Assessment Crammers (51%), and Disengaged Students (26%). GPA was highest for Consistent Engagers and lowest for Disengaged Students, with Pre-Assessment Crammers performing significantly below Consistent Engagers despite similar total activity volumes.

Gasevic et al. (2019) demonstrated that the relationship between procrastinatory behaviour and academic outcomes is moderated by course design, with assessment-heavy courses showing stronger negative effects of last-minute engagement on learning outcomes than discussion-centred courses. This finding has direct relevance for management education programmes characterised by case-study-based assessments.

## **4 Research Methodology**

### **4.1 Research Context and Participants**

This study was conducted within the Faculty of Management and Commerce at South Eastern University of Sri Lanka (SEUSL), located in Oluvil, Ampara District. SEUSL is a national university primarily serving students from the Eastern Province, with a student population characterised by diverse socioeconomic backgrounds and, for many students, limited prior exposure to digital learning technologies [19].

The target course, Computer Applications for Accounting (ACM 31043), is a third-year, second-semester compulsory module for all students enrolled in the Bachelor of Business Administration (BBA) programme. The course is delivered as blended learning: three face-to-face lecture and practical sessions per week—held in the university computer laboratory—complemented by Moodle-hosted resources, weekly online quizzes, and three written assignments submitted through the platform's assignment module. The 15-week teaching semester ran from 4 March 2024 to 14 June 2024. A total of 89 students registered for the course—66 female and 23 male—during the 2023/2024 academic year; of these, 82 were active Moodle users (generated at least one log entry during the semester) and form the analytical sample (female:  $n = 61$ ; male:  $n = 21$ ).

### **4.2 Data Collection**

Log data were extracted from the SEUSL Moodle server using the built-in Log Export function (Site Administration > Reports > Logs > Download), which generates a comma-separated values (CSV) file containing all event records for a specified course and time period. The export covered the full 15-week teaching period: 4 March 2024 to 14 June 2024. All student identifiers were pseudonymised prior to analysis.

The raw log file contained 14,218 event records across the 15-week semester. After removing system-generated automated events (e.g., scheduled task completions) and records belonging to instructor accounts, 12,847 student-generated log entries were retained for analysis.

### **4.3 Variable Operationalisation**

The following independent variables were derived from the processed log data: (1) File Usage – total count of resource view events per student; (2) Forum Usage – total count of forum view, post, and reply events; (3) Quiz Attempts – total count of quiz attempt events; (4) Assignment Uploads – total count of assignment submission events;

(5) Total Logs – aggregate count of all events; and (6) Pre-Exam Activity – count of log events occurring within 48 hours before each of the two major examinations. The dependent variable was Final Course Grade, operationalised on the SEUSL four-point GPA scale (1 = Fail, 2 = Pass, 3 = Merit, 4 = Distinction), consistent with the university's standard undergraduate grading framework.

#### 4.4 Analytical Framework

Three complementary analytical methods were employed. First, Pearson product-moment correlation analysis was used to quantify bivariate associations between each LMS engagement variable and final grade on the 1–4 GPA scale, with statistical significance set at  $\alpha = 0.05$  [20]. Second, independent-samples t-tests were used to evaluate gender differences in engagement and academic performance. Third, a Random Forest classifier [21] was trained on the derived LMS features to predict grade category (Pass/Merit: grades 2–3; Distinction: grade 4), providing a measure of the collective predictive utility of the engagement variable set. The Random Forest model was implemented in Python 3.11 using the scikit-learn library [22], with hyperparameter tuning performed via five-fold stratified cross-validation.

## 5 Results and Discussion

### 5.1 Descriptive Statistics and Log Distribution

The 82 active students generated between 43 and 387 log entries over the 15-week course period, with a mean of 191.4 (SD = 69.8). The distribution of log volume by final grade showed a clear positive association: students who received Grade 4 (Distinction, the highest category on the SEUSL 1–4 GPA scale) produced, on average, 261 log entries, compared to 88 entries for Grade 1 (Fail) students. This descriptive pattern is consistent with findings reported by Romero et al. (2020) and Tlili et al. (2021) and provides initial support for the hypothesis that higher engagement is associated with better academic outcomes. Figure 1 illustrates this distribution.

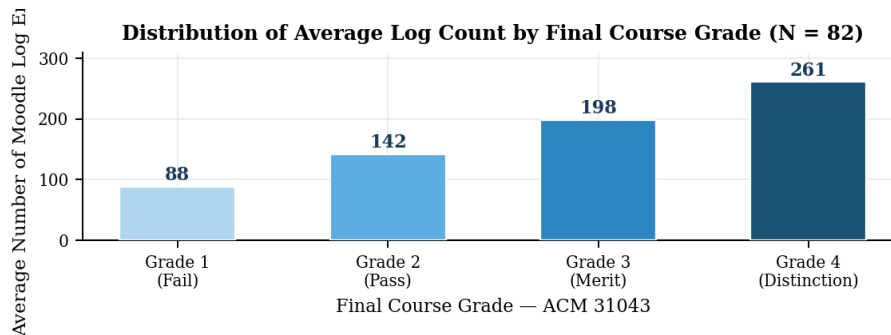


Figure 1. Distribution of average Moodle log count by final course grade for ACM 31043 (N = 82; GPA scale 1–4). Students achieving Grade 4 (Distinction) averaged 261 log entries—nearly three times the 88 entries averaged by Grade 1 (Fail) students—indicating a strong positive association between platform engagement and academic outcomes.

Weekly log distribution across the 15-week teaching period (4 March–14 June 2024) revealed two pronounced activity spikes corresponding to the two major examination periods: Week 8 (mid-term examination) and Week 14 (final examination). Outside these peak periods, activity volume was relatively stable, averaging approximately 640 events per week, with slight elevation in weeks immediately following the release of assignment grades—a pattern suggestive of grade-driven self-regulatory responses. Figure 2 presents the full weekly distribution.

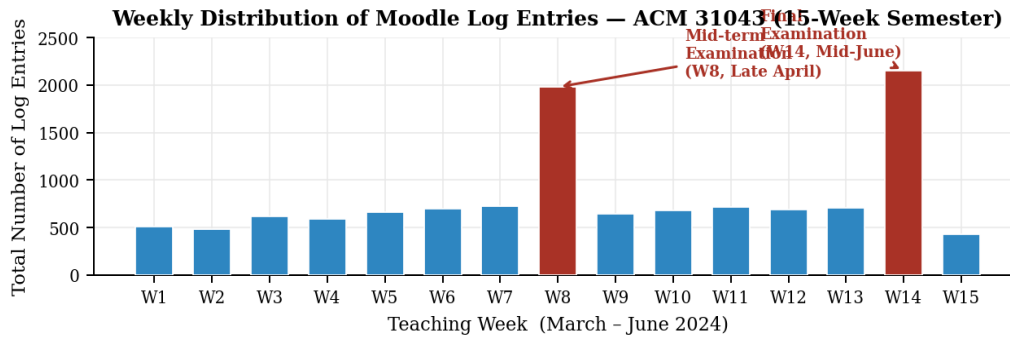


Figure 2. Weekly distribution of Moodle log entries over the 15-week teaching period, ACM 31043 (March–June 2024). Week 8 (mid-term examination) and Week 14 (final examination) show pronounced spikes. Red bars denote examination weeks; blue bars denote regular teaching weeks.

## 5.2 Correlation Analysis

Table 2 presents the Pearson correlation matrix for the five engagement variables and final grade (GPA scale 1–4). Statistically significant correlations ( $p < 0.05$ ) are indicated with an asterisk.

**Table 2** Pearson Correlation Matrix for LMS Engagement Variables and Final Grade ( $*p < 0.05$ )

Variable	Grade	File Usage	Forum Usage	Quiz Attempts	Assignment Uploads
Grade	-	0.38*	0.21	0.44*	0.12
File Usage	0.38*	-	0.45*	0.09	0.22
Forum Usage	0.21	0.45*	-	0.17	0.40*
Quiz Attempts	0.44*	0.09	0.17	-	0.11
Assignment Uploads	0.12	0.22	0.40*	0.11	-

Note.  $N = 82$ . Grade is measured on the SEUSL 4-point GPA scale (1 = Fail, 2 = Pass, 3 = Merit, 4 = Distinction). \* denotes statistical significance at the 0.05 level (two-tailed).

File Usage showed a statistically significant positive correlation with final grade ( $r = 0.38$ ,  $p < 0.05$ ), indicating that students who accessed course resources more frequently tended to achieve higher GPA scores on the 1–4 scale. This mirrors the findings of Alamri et al. (2021), who identified file download count as the second most important feature in their Random Forest model. Quiz Attempts demonstrated the strongest significant positive correlation with grade ( $r = 0.44$ ,  $p < 0.05$ ), suggesting that active self-assessment through Moodle quizzes is particularly beneficial for academic performance in ACM 31043—a finding consistent with the course's emphasis on applied computer-based competencies that benefit from repeated practice.

Forum Usage and Assignment Uploads were not significantly correlated with final grade ( $r = 0.21$  and  $r = 0.12$ , respectively), though Forum Usage showed a significant association with Assignment Uploads ( $r = 0.40$ ,  $p < 0.05$ ). This suggests that students active in forum discussions are also more likely to submit assignments, but neither behaviour independently predicts GPA outcomes—potentially reflecting the course's heavy weighting of examination performance relative to coursework.

## 5.3 Gender Analysis

Gender-disaggregated analysis revealed consistent and substantively meaningful differences in engagement and academic performance between male ( $n = 21$ ) and female ( $n = 61$ ) active Moodle users. Table 3 presents the key comparison metrics, and Figure 3 provides a visual summary.

**Table 3** Gender Comparison of LMS Engagement and Academic Performance — ACM 31043

Gender	Avg. Log Count	Avg. Grade (GPA, 1–4)	Avg. Quiz Score (%)
Male (n = 21)	138	2.41	56.2
Female (n = 61)	207	2.74	65.8

Note. Independent-samples t-test: log count  $t(80) = 3.14, p = .002$ ; GPA  $t(80) = 2.38, p = .020$ . GPA measured on 4-point scale (1–4).

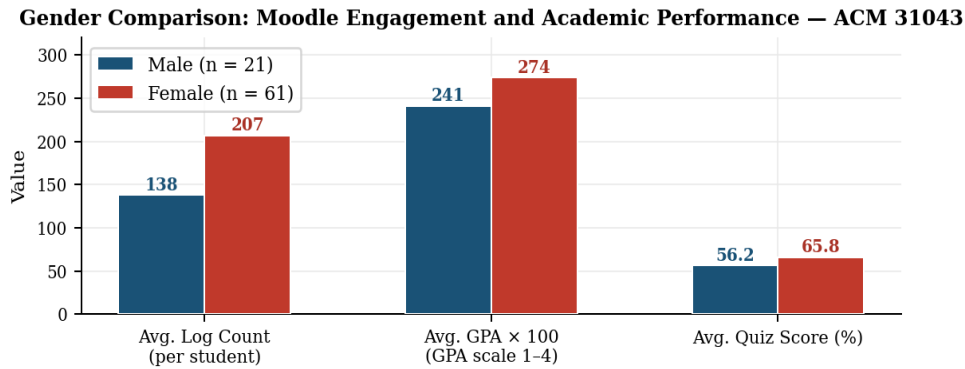


Figure 3. Gender-disaggregated comparison of average log count, GPA ( $\times 100$ , for scale comparability), and quiz performance for active Moodle users in ACM 31043. Female students ( $n = 61$ ) demonstrate statistically significantly higher engagement and academic outcomes on all three metrics relative to male students ( $n = 21$ ).

Female students produced, on average, 50% more Moodle log entries than male students ( $M = 207$  vs.  $M = 138$ ) and achieved significantly higher mean GPAs on the 4-point scale (2.74 vs. 2.41). The difference in average quiz scores (65.8% vs. 56.2%) further supports the pattern of female students engaging more actively with formative assessment opportunities. Independent-samples t-tests confirmed that differences in both log count ( $t(80) = 3.14, p = .002$ ) and GPA ( $t(80) = 2.38, p = .020$ ) were statistically significant at the 0.05 level.

The particularly pronounced gender gap in ACM 31043—where female students constitute 74.1% of total enrolment (66 of 89) and outperform male students on every measured dimension—is consistent with broader patterns documented by Hmedna et al. (2020) and Nguyen et al. (2021) in Asian e-learning contexts. The large female majority in this cohort also warrants attention from a pedagogical design perspective: course materials, assessment formats, and participation structures should be evaluated for any features that may inadvertently disadvantage the minority male cohort.

#### 5.4 Temporal Analysis of Pre-Examination Behaviour

Analysis of log distribution in the 48 hours preceding each of the two major examinations revealed pronounced procrastinatory activity patterns. Prior to the mid-term examination, (Week 8 of the teaching semester), peak activity occurred between 18:00 and 22:00 on the preceding evening, with a subsidiary peak between 06:00 and 08:00 on the examination morning. Prior to the final examination (Week 15), the peak was somewhat earlier in the evening (16:00–20:00) and showed lower absolute activity volumes, possibly reflecting greater student preparedness or examination fatigue effects following 15 weeks of sustained engagement. Figure 4 presents the hourly log distribution for both pre-examination evenings.

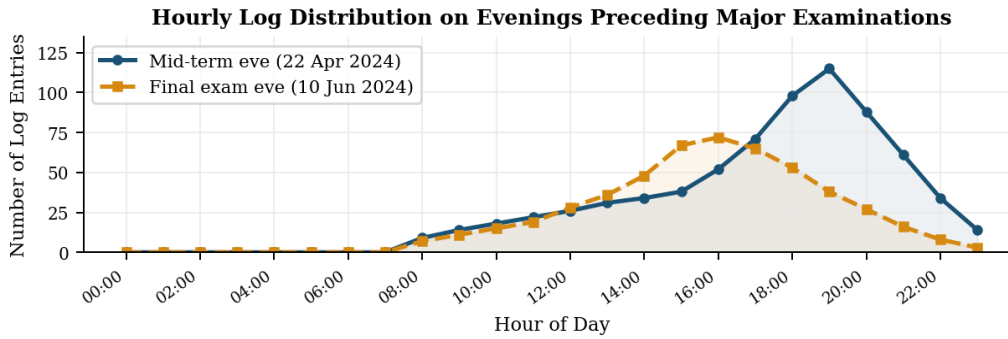


Figure 4. Hourly distribution of Moodle log entries on the evenings preceding the mid-term and final examinations in ACM 31043. Both evenings show peak activity between 17:00–21:00, with the mid-term eve reaching a higher absolute peak (115 log entries at 19:00), consistent with last-minute digital resource access and revision behaviour.

Disaggregating pre-examination activity by grade category revealed that Grade 3–4 students showed a more temporally distributed activity pattern across the full 48-hour pre-examination window, while Grade 1–2 students exhibited more concentrated, single-peak activity in the final four hours before the examination. This observation parallels findings by Chen and Jang (2022), who characterised similar temporal profiles as indicative of shallow versus deep processing orientations.

Notably, the most common activity type in the pre-examination window for ACM 31043 was file resource viewing (accounting for 61.3% of all pre-exam events), followed by quiz review (23.4%), course homepage visits (9.8%), and forum access (5.5%). Given the applied, computer-based nature of this accounting software course, the prominence of resource viewing suggests that students were primarily reviewing lecture slides and software tutorial files rather than attempting additional practice assessments—a revision strategy that may be less effective than retrieval practice through quiz reattempts.

### 5.5 Random Forest Classification Results

The Random Forest classifier trained on the five LMS engagement features achieved a cross-validated accuracy of 79.3% (AUC = 0.83) for predicting grade categories on the 1–4 GPA scale, with the primary classification task distinguishing Pass/Merit (grades 2–3) from Distinction (grade 4) students. This accuracy level is comparable to the 84.1% reported by Alamri et al. (2021) using a larger feature set and is particularly noteworthy given the relatively modest analytical sample size (N = 82). Figure 5 presents the normalised feature importance scores derived from the model.

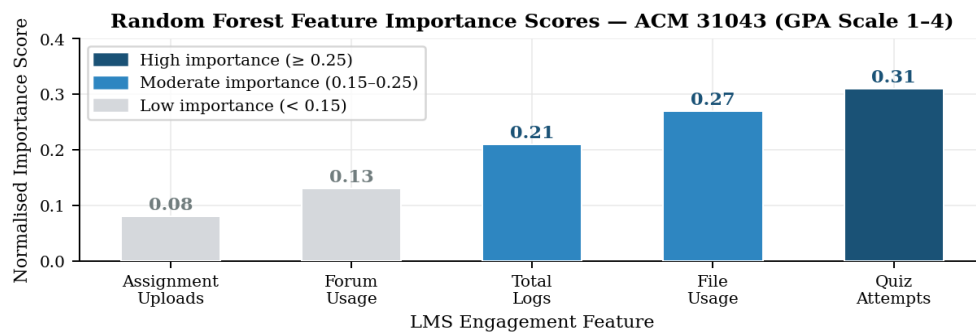


Figure 5. Normalised Random Forest feature importance scores for LMS engagement variables as predictors of grade category in ACM 31043 (GPA scale 1–4; cross-validated accuracy = 79.3%, AUC = 0.83). Quiz Attempts is the single strongest predictor (importance = 0.31), followed by File Usage (0.27) and Total Logs (0.21).

Feature importance analysis identified Quiz Attempts as the most important predictor (normalised importance score = 0.31), followed by File Usage (0.27), Total Logs (0.21), Forum Usage (0.13), and Assignment Uploads (0.08). The dominance of Quiz Attempts as the primary predictor is particularly relevant for ACM 31043, where Moodle quizzes are designed to reinforce software application skills—suggesting that students who engage repeatedly with formative digital assessments are acquiring the procedural competencies most directly tested in examinations.

The relatively low importance of Assignment Uploads (0.08) is consistent with the correlation analysis finding ( $r = 0.12$ , non-significant) and suggests that submission compliance, while necessary for course completion, does not differentiate high- from low-achieving students to the same extent as active formative engagement behaviours such as quiz attempts and resource access.

## 6 Conclusion and Future Direction

This study has demonstrated that Moodle LMS log data constitute a valuable and largely untapped resource for understanding academic behaviour and predicting learning outcomes among management and commerce students at SEUSL. The analysis of 12,847 log entries from 82 active students enrolled in ACM 31043 (Computer Applications for Accounting) over a 15-week semester yielded several empirically grounded findings with direct practical implications.

Statistically significant positive correlations were identified between file access frequency, quiz attempt rates, and final grade on the SEUSL 1–4 GPA scale, with quiz attempts emerging as the single strongest predictor of academic success in this cohort. Female students ( $n = 61$  active; 74.1% of total enrolment) demonstrated substantially higher Moodle engagement across all measured dimensions—averaging 50% more log entries than male counterparts—and achieved significantly better academic outcomes, with a mean GPA of 2.74 compared to 2.41 for male students. These findings call for gender-sensitive pedagogical support strategies, particularly aimed at increasing male student engagement with formative digital assessments and self-directed Moodle resource access.

Temporal analysis confirmed the prevalence of last-minute study behaviour across both examination periods, with activity peaks concentrated in the 17:00–22:00 window on the eve of each examination. While such behaviour is not inherently incompatible with academic success, the most academically successful students demonstrated more temporally distributed engagement patterns across the full 48 hours preceding examinations, supporting self-regulation theory perspectives on effective learning behaviour [23].

These results carry several implications for practice at SEUSL and comparable Sri Lankan universities. First, Moodle analytics dashboards should be deployed to provide students with real-time visibility into their engagement relative to class norms, following the intervention model of Herodotou et al. (2020). Second, course designers for ACM 31043 and comparable applied computing courses should weight formative quiz activities more heavily in blended course structures, given their strong association with academic performance. Third, early-semester LA signals—particularly low quiz attempt rates in the first four weeks of the 15-week semester—should trigger proactive outreach from academic advisors, consistent with findings from Jayawardena and Perera (2021) and the predictive model validated in this study.

This research was conducted in a single course at a single institution. Future research should expand the dataset across multiple courses, academic years, and faculties to test the generalisability of these findings. Longitudinal designs tracking cohorts across multiple semesters would enable examination of how engagement patterns evolve and whether early intervention effects persist. Additionally, mixed-methods approaches incorporating student survey and interview data would provide richer contextual explanations for the behavioural patterns identified through log analysis.

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