BG Pulse Journal USA
ISSN:1947-2536 http://www.bgpulseusa.com/index.php/bg
BG PULSE JOURNAL

DEVELOPMENT OF A SOFTWARE TOOL FOR MONITORING STUDENTS' SUBJECT MASTERY BASED ON MOODLE LMS

Egamberdiyeva Shaxina Ulugbek qizi

Master's student at Bukhara State University

Doi: https://doi.org/10.5281/zenodo.22147209

Abstract: The rapid expansion of e-learning and blended instruction in higher education has increased reliance on Learning Management Systems (LMS), among which Moodle remains the most widely deployed open-source platform. Despite its extensive built-in logging capabilities, Moodle provides limited native functionality for the systematic, real-time monitoring of individual and group-level subject mastery across a semester. This study presents the design, implementation, and empirical evaluation of a software monitoring tool developed as a Moodle-integrated web module that aggregates quiz scores, assignment grades, attendance records, and activity-log data into a composite Subject Mastery Index (SMI) for each student and course. The tool was implemented using the Moodle Web Services REST API for data extraction, a relational database for analytical storage, and a browser-based dashboard for visualization. The system was piloted over one academic semester with 214 students enrolled in six courses at a technical university. Results indicate that the tool identified at-risk students on average 3.4 weeks earlier than end-of-term grading, that instructors using the dashboard increased the frequency of formative feedback by 47%, and that the proportion of students classified as having achieved satisfactory subject mastery rose from 68.1% to 81.3% in the intervention group compared with a 3.9-percentage-point change in the control group. These findings suggest that lightweight, LMS-integrated monitoring tools can meaningfully support early intervention and evidence-based teaching decisions without requiring institutions to replace their existing LMS infrastructure.

Keywords: Moodle LMS, learning analytics, academic performance monitoring, educational data mining, e-learning, student dashboard, higher education, early-warning system.

1. Introduction

Digital transformation has become a defining feature of contemporary higher education, and Learning Management Systems (LMS) now serve as the primary infrastructure through which course content, assessment, and communication are delivered. Among the available platforms, Moodle occupies a distinctive position: it is open-source, highly customizable, and used by tens of thousands of educational institutions worldwide, including a large share of universities in Uzbekistan following the accelerated digitalization of the national higher-education system. Moodle records a substantial volume of granular data on every student interaction — quiz attempts, assignment submissions, forum participation, resource views, and login timestamps — through its internal logging subsystem.

Despite the richness of this underlying data, Moodle's default reporting tools present information in a fragmented, course-by-course, activity-by-activity manner. Instructors and academic administrators who wish to answer a seemingly simple question — which students are falling behind in mastering the subject, and in which competencies specifically — must manually cross-reference multiple reports, a process that is time-consuming, error-prone, and typically

performed too late to allow meaningful pedagogical intervention. This gap between data availability and actionable insight is well documented in the learning-analytics literature and constitutes the central motivation for the present study.

The specific problem addressed in this paper is the absence, within standard Moodle deployments, of a unified, real-time, course-level and program-level monitoring instrument that (a) synthesizes heterogeneous performance indicators into a single interpretable mastery measure, (b) flags students at risk of academic underperformance sufficiently early for corrective action, and (c) presents this information through a dashboard interface usable by non-technical academic staff.

The aim of this research was therefore twofold: first, to design and implement a software tool — built on top of Moodle's Web Services API rather than requiring modification of Moodle's core — capable of continuously monitoring students' subject mastery across courses; and second, to empirically evaluate the effect of this tool on the timeliness of at-risk identification, instructor feedback behavior, and end-of-semester academic outcomes. The remainder of the paper is organized following the IMRAD structure: Section 2 describes the system architecture, the mastery-scoring methodology, and the evaluation design; Section 3 reports the results of the pilot deployment; Section 4 discusses these findings in relation to prior work and outlines limitations; and Section 5 concludes with implications for practice and directions for future research.

2. Materials and Methods

2.1. System Architecture

The monitoring tool was designed as a loosely coupled, three-layer web application: (1) a data-extraction layer that communicates with Moodle exclusively through the standard Moodle Web Services REST API (functions such as core_course_get_contents, mod_quiz_get_user_attempts, mod_assign_get_submissions, and core_completion_get_activities_completion_status), thereby avoiding any modification of Moodle core code; (2) an analytical and storage layer implemented in PostgreSQL, which periodically synchronizes extracted records via a scheduled ETL (extract–transform–load) service and computes derived indicators; and (3) a presentation layer — a responsive web dashboard built with a JavaScript charting library — through which instructors, department heads, and academic-affairs staff access student- and group-level reports. Authentication and role-based access control were delegated to Moodle's existing OAuth2/token infrastructure so that no parallel account system was required.

This architecture was deliberately chosen over a native Moodle plugin (block or report plugin written in PHP) to ensure portability across Moodle versions and to decouple the analytical logic from Moodle's release cycle, at the cost of near-real-time (rather than truly real-time) data synchronization; the ETL service was configured to run every 30 minutes during the pilot.

2.2. Subject Mastery Index (SMI)

For each student i in course c, a composite Subject Mastery Index was computed as a weighted combination of four indicators normalized to a 0–100 scale:

$$SMIic = w_1 \cdot Qic + w_2 \cdot Aic + w_3 \cdot Eic + w_4 \cdot Cic$$

where Q denotes the normalized average quiz score, A the normalized average assignment grade, E an engagement score derived from log-in frequency, resource views, and forum participation relative to course peers, and C the proportion of course learning outcomes marked complete in Moodle's Activity Completion module. Weights (w_1=0.40, w_2=0.35, w_3=0.10, w_4=0.15) were set in consultation with the participating instructors and calibrated so that the weighted sum correlated most strongly (Pearson r = 0.81) with final course grades from the two preceding semesters, used as a validation benchmark. Students were classified into three mastery bands — Satisfactory (SMI ≥ 70), Borderline (55 ≤ SMI < 70), and At-Risk (SMI < 55) — with the At-Risk band triggering an automated notification to the instructor and academic advisor.

2.3. Participants and Study Design

The tool was piloted during one 15-week academic semester at a technical university in Uzbekistan. A total of 214 students across six undergraduate courses (two in computer engineering, two in applied mathematics, and two in general education) were included. Courses were paired by discipline and prior-semester grade distribution and quasi-randomly assigned to an intervention group (n = 108 students, three courses) in which instructors had access to the monitoring dashboard, and a control group (n = 106 students, three courses) in which instructors continued to rely on Moodle's standard gradebook and reports. Instructors in both groups received the same assessment schedule and grading rubrics.

Three outcome measures were defined a priori: (1) time-to-identification, measured as the number of weeks between a student's SMI first falling into the At-Risk band and the corresponding instructor recording a documented intervention (e.g., outreach message, remedial task, advising referral) in either group's available system; (2) feedback frequency, the number of individualized formative feedback instances (comments, messages, or grading annotations) recorded per instructor per week; and (3) end-of-semester mastery attainment, the proportion of students in each group whose final course grade corresponded to a Satisfactory mastery classification. Between-group comparisons used independent-samples t-tests and chi-square tests of proportions, with statistical significance set at $\alpha = 0.05$.

3. Results

Over the semester, the ETL pipeline processed an average of 38,600 Moodle log and grade records per week without measurable degradation of LMS response times, confirming the feasibility of API-based extraction at this institutional scale.

3.1. Time-to-Identification of At-Risk Students

In the intervention group, the monitoring dashboard flagged 31 students as At-Risk at some point during the semester, at an average of 5.8 weeks into the 15-week term. Documented instructor intervention followed within an average of 1.2 weeks of the flag. In the control group, an equivalent set of 29 students eventually fell into the same performance band by end-of-semester grade analysis, but the corresponding instructor intervention (where it occurred at all) was recorded on average 4.6 weeks into remaining course time — i.e., considerably closer to the end of the semester. The difference in time-to-identification between groups was 3.4 weeks on average (t(58)

= 6.12, $p < 0.001$), consistent with the central hypothesis that continuous SMI monitoring accelerates the detection of struggling students relative to conventional periodic grading.

3.2. Instructor Feedback Frequency

Instructors in the intervention group recorded a mean of 4.4 individualized feedback instances per week per course, compared with 3.0 in the control group, a 47% relative increase ($t(4) = 3.85$, $p = 0.018$). Instructors using the dashboard reported, in a post-semester survey, that the consolidated view of quiz, assignment, engagement, and completion data reduced the time required to identify which students needed attention.

3.3. End-of-Semester Mastery Attainment

The proportion of students classified as achieving Satisfactory mastery increased from 68.1% (pre-semester baseline, derived from prior-semester grades of the same cohort) to 81.3% in the intervention group — a 13.2-percentage-point increase. In the control group, the corresponding change was from 66.7% to 70.6%, a 3.9-percentage-point increase. The between-group difference in improvement was statistically significant ($\chi^2 = 9.47$, $df = 1$, $p = 0.002$), summarized in Table 1.

Indicator	Intervention group (n=108)	Control group (n=106)
Satisfactory mastery — start of semester	68.1%	66.7%
Satisfactory mastery — end of semester	81.3%	70.6%
Mean time-to-identification (weeks)	5.8 (flag) / 1.2 (response)	— / 4.6 (response)
Mean instructor feedback per week	4.4	3.0

Table 1. Summary of pilot-study outcome measures by group.

4. Discussion

The results of this pilot deployment support the hypothesis that a lightweight, API-based monitoring layer built on top of an existing Moodle installation can materially improve the timeliness and frequency of pedagogical intervention without requiring institutions to migrate to a different LMS or to modify Moodle's core codebase. The 3.4-week average acceleration in at-risk identification is comparable to gains reported in earlier learning-analytics early-warning systems such as Course Signals and OU Analyse, suggesting that the composite-index approach used here

— despite its comparative simplicity relative to machine-learning-based predictive models — is sufficient to produce practically meaningful improvements in a resource-constrained institutional setting.

The observed increase in instructor feedback frequency is consistent with the broader learning-analytics literature indicating that dashboards primarily change teaching practice by reducing the cognitive and administrative burden of locating relevant information, rather than by providing predictions instructors could not otherwise infer. This has practical implications for institutions in Uzbekistan and comparable contexts: the marginal cost of deploying such a tool is modest — it requires no proprietary LMS features, relies entirely on Moodle's public Web Services API, and can be hosted on standard university server infrastructure — while the pedagogical return, at least in this pilot, appears substantial.

Several limitations should be noted. First, the pilot was conducted at a single institution over a single semester with a quasi-experimental rather than fully randomized design, limiting causal inference; course-level rather than individual-level assignment to condition also introduces the possibility of confounding by instructor characteristics. Second, the weighting scheme for the Subject Mastery Index, while empirically calibrated against two prior semesters, was not validated across disciplines outside computer engineering, mathematics, and general education, and may require recalibration for courses with different assessment structures (e.g., studio- or laboratory-based courses). Third, the engagement component of the index, based on log-in and resource-view counts, is a behavioral proxy rather than a direct cognitive measure and may disadvantage students who study effectively offline. Finally, the 30-minute synchronization interval, while adequate for weekly-cycle interventions, would need to be reduced for use cases requiring intra-day alerting.

Future work should extend the evaluation to a multi-institutional, randomized design; explore replacing the fixed-weight linear index with a machine-learning classifier trained on a larger longitudinal dataset while preserving interpretability for instructors; and investigate the integration of qualitative indicators, such as peer- and self-assessment data, into the mastery score.

5. Conclusion

This study designed, implemented, and empirically evaluated a Moodle-integrated software tool for monitoring students' subject mastery, built entirely on Moodle's public Web Services API and requiring no modification of the LMS core. Piloted with 214 students across six courses, the tool reduced the time required to identify at-risk students by an average of 3.4 weeks, increased instructor feedback frequency by 47%, and was associated with a substantially larger improvement in end-of-semester subject-mastery attainment relative to a matched control group. These findings indicate that low-cost, API-based analytics layers can meaningfully strengthen formative assessment practice within existing Moodle deployments, offering a practical model for universities — particularly in resource-constrained settings such as Uzbekistan's rapidly digitalizing higher-education sector — seeking to improve early intervention without large-scale infrastructure investment.

References

1. Dougiamas, M., Taylor, P. (2003). Moodle: Using Learning Communities to Create an Open Source Course Management System. Proceedings of EdMedia+ Innovate Learning, 171–178.

2. Siemens, G. (2013). Learning Analytics: The Emergence of a Discipline. American Behavioral Scientist, 57(10), 1380–1400.
3. Romero, C., Ventura, S. (2020). Educational Data Mining and Learning Analytics: An Updated Survey. WIREs Data Mining and Knowledge Discovery, 10(3), e1355.
4. Arnold, K. E., Pistilli, M. D. (2012). Course Signals at Purdue: Using Learning Analytics to Increase Student Success. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, 267–270.
5. Herodotou, C., et al. (2019). A Large-Scale Implementation of Predictive Learning Analytics in Higher Education: The Teachers' Role and Perspective. Educational Technology Research and Development, 67(5), 1273–1306.
6. Rienties, B., Toetenel, L. (2016). The Impact of Learning Design on Student Behaviour, Satisfaction and Performance: A Cross-Institutional Comparison across 151 Modules. Computers in Human Behavior, 60, 333–341.
7. Tempelaar, D. T., Rienties, B., Giesbers, B. (2015). In Search for the Most Informative Data for Feedback Generation: Learning Analytics in a Data-Rich Context. Computers in Human Behavior, 47, 157–167.
8. Sclater, N., Peasgood, A., Mullan, J. (2016). Learning Analytics in Higher Education: A Review of UK and International Practice. Jisc, Bristol.
9. Moodle Pty Ltd. (2024). Moodle Web Services API Documentation. Retrieved from https://docs.moodle.org/dev/Web_service_API_functions
10. Karimov, I., Yusupov, R. (2022). Digitalization of Higher Education in Uzbekistan: Current State and Prospects. Journal of Educational Technology Development and Exchange, 15(2), 45–58.