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Comparing Learning Analytics-Supported and Traditional Mathematics Instruction across Higher Education Institutions in Afghanistan

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A B S T R A C T

Learning analytics (LA)-supported instruction has shown promise for improving student engagement, yet empirical evidence from infrastructure-constrained higher education systems remains limited. This study addresses that gap by pursuing two objectives: first, to compare mathematics achievement between students taught using LA-supported technology-based instruction and students taught using traditional lecture-based instruction at Samangan University, Afghanistan; and second, to examine the extent to which learning analytics engagement indicators login frequency, video time-on-task, quiz attempts, and forum participation predict students' mathematics achievement. A quasi-experimental, nonequivalent control-group, pretest–posttest design was employed with 96 second-year mathematics education students across two intact sections (experimental $n = 48$; control $n = 48$) over a 14-week term. Data were analyzed using independent-samples t-tests, analysis of covariance (ANCOVA), Pearson correlations, and multiple regression. Students in the LA-supported condition achieved significantly higher posttest scores ($M = 78.6$, $SD = 7.4$) than those in the traditional condition ($M = 65.2$, $SD = 9.0$), $t(94) = 7.42$, $p < .001$, $d = 1.52$, an advantage that remained significant after adjusting for pretest differences, $F(1, 93) = 54.87$, $p < .001$, partial $\eta^2 = .37$. Among the engagement indicators, video time-on-task ($\beta = .34$, $p = .004$) and quiz attempts ($\beta = .27$, $p = .024$) emerged as significant independent predictors, with the full set of indicators jointly accounting for 46% of the variance in posttest scores (adjusted $R^2 = .41$). Although the nonrandomized design limits causal inference, these findings extend empirical evidence on LA-supported mathematics instruction to a resource-constrained, fragile-state higher education context and indicate that behaviorally substantive engagement is a more informative predictor of achievement than platform access alone.

1. Introduction

Mathematics achievement remains one of the most persistent challenges facing higher education systems in post-conflict and resource-constrained countries, and Afghanistan is no exception. Despite ongoing efforts by the Ministry of Higher Education to reform curricula and improve instructional quality, many mathematics classrooms across Afghan public universities continue to rely almost exclusively on traditional, teacher-centered lecture methods, in which students play a largely passive role and receive limited individualized feedback (Katawazai, 2021; Oryakhail et al., 2021). At the same time, the global expansion of learning management systems (LMS) and learning analytics (LA) tools has opened new possibilities for monitoring, understanding, and improving how students learn, offering instructors real-time, data-informed insight into engagement patterns that were previously invisible (Long & Siemens, 2011; Siemens, 2013).

Learning analytics is broadly defined as the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Long & Siemens, 2011; Siemens, 2013). When embedded within an LMS, an LA dashboard can capture fine-grained behavioral traces, such as login frequency, time spent on instructional videos, number of quiz attempts, and participation in discussion forums, that serve as proxies for student engagement and, ultimately, for academic performance (Gasevic et al., 2015; Viberg et al., 2018). A substantial body of research has demonstrated that technology-enhanced instruction, when appropriately designed, is associated with improved mathematics learning outcomes relative to traditional instruction (Cheung & Slavin, 2013; Li & Ma, 2010), and that engagement indicators captured through LA systems correlate meaningfully with achievement (Ifenthaler & Yau, 2020; Papamitsiou & Economides, 2014; Chen et al., 2023). More recent systematic evidence tempers earlier optimism, however: a 2024 review of the impact of LA dashboards on achievement, motivation, and participation found that most existing studies report negligible-to-small effects, with measurable achievement benefit occurring mainly when substantive behavioral engagement, rather than mere dashboard access, is present (Kaliisa et al., 2024). This tempered picture strengthens, rather than weakens, the case for context-specific quasi-experimental evidence, since the conditions under which LA-supported instruction does or does not translate into achievement gains remain empirically unsettled, and prior studies vary considerably in research design, educational level, type of technology, and outcome measures.

However, most empirical evidence on learning analytics and technology-based mathematics teaching originates from well-resourced educational systems in North America, Europe, and parts of Asia (Bond et al., 2019; Viberg et al., 2018; Kaliisa et al., 2023). Considerably less is known about how LA-supported technology-based instruction performs relative to traditional teaching in fragile, infrastructure-constrained contexts such as Afghanistan, where unstable internet connectivity, limited digital literacy among both lecturers and students, and heavy reliance on conventional lecture methods remain widespread (Musawi & Baktash, 2021; Rahim & Sandaran, 2020; Noori et al., 2022; Abou-Khalil et al., 2021). This gap is particularly consequential for mathematics education, a discipline in which timely feedback and sustained practice are strongly associated with achievement gains (Bray & Tangney, 2017; Kebritchi et al., 2010).

Samangan University, located in northern Afghanistan, represents a typical case of a provincial public university seeking to modernize its instructional practices amid significant resource constraints. To the authors' knowledge, based on the literature reviewed for this study, no empirical study has directly compared traditional and LA-supported technology-based mathematics teaching within this specific institutional context, nor examined which learning analytics indicators most strongly predict achievement among Afghan mathematics education students. Addressing this gap is important both theoretically, by extending the learning analytics literature to an underexplored fragile-state setting, and practically, by providing Afghan higher education policymakers and instructors with locally grounded evidence to guide technology adoption decisions (Trucano, 2005; Selwyn, 2016).

This study contributes to the literature in three ways. First, it provides a quasi-experimental comparison of LA-supported and traditional mathematics teaching in a fragile-state university context where such comparisons have not previously been documented. Second, it examines four behavioral LA indicators login frequency, video time-on-task, quiz attempts, and forum participation simultaneously as predictors of achievement, offering contextual evidence on whether behaviorally substantive engagement remains more informative than mere platform access under infrastructure constraints. Third, it links technology use to mathematics achievement in Afghanistan specifically, an outcome–subject combination not previously examined empirically in this setting.

Accordingly, this study pursues two research objectives. The first objective is to compare mathematics achievement between students taught using LA-supported technology-based instruction and students taught using traditional lecture-based instruction at Samangan University. The second objective is to examine the extent to which learning analytics engagement indicators login frequency, video-lecture time-on-task, quiz attempts, and forum participation predict students' mathematics achievement among students in the technology-based condition.

1.1. Conceptual Framework

Figure 1 illustrates the conceptual framework guiding the study. The instructional condition (technology-based versus traditional teaching) constitutes the independent variable. Because the four learning analytics indicators are generated by the Moodle-based dashboard, they are captured only within the technology-based condition; together with prior achievement as a covariate, these indicators are hypothesized to be associated with rather than to causally determine students' mathematics learning achievement in the experimental group specifically. This framework is presented prior to the Method because it is conceptual rather than an empirical finding of the study, and the relationships it depicts follow directly from the learning analytics and technology-enhanced mathematics education literature reviewed above, particularly the distinction between behaviorally substantive engagement and passive platform access (Gasevic et al., 2015; Kaliisa et al., 2024).

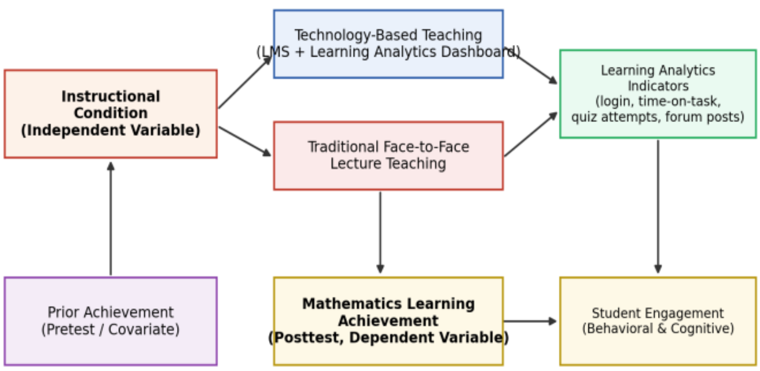

Figure 1. Conceptual framework linking instructional condition, learning analytics indicators, and mathematics achievement.

2. Methods

This study employed a quasi-experimental, nonequivalent control-group, pretest–posttest design (Cook & Campbell, 1979; Shadish et al., 2002). Random assignment of individual students was not feasible because the students were already enrolled in two pre-existing, intact class sections; the design therefore compares two naturally occurring groups while statistically controlling for pretest differences through ANCOVA.

2.1. Research Design

Two intact sections of second-year students enrolled in a core Calculus and Applied Statistics course at the Department of Mathematics Education, Samangan University, were assigned, by section, to an experimental condition (technology-based teaching supported by a learning analytics dashboard) and a control condition (traditional lecture-based teaching). Assignment of the two available intact sections to these conditions was administrative rather than randomized: both sections had already been formed prior to the study through standard departmental registration and timetabling, and the section designated as the experimental (technology-based) condition was the section scheduled into the classroom equipped with the fixed computer workstations and stable networked access needed to run the LMS and dashboard; the control section met in a standard lecture room without this equipment. Because allocation was not randomized at the individual or section level, the design is appropriately classified as a nonequivalent control-group design, and pretest scores were used as a covariate in ANCOVA to statistically adjust for baseline differences between groups. Both sections were taught by the same instructor across the full semester, who followed a shared weekly lesson-pacing guide and an identical set of learning objectives in both sections, differing only in delivery mode; content coverage was cross-checked against the syllabus schedule at the midpoint and end of the term to confirm pacing had remained aligned. Both groups followed an identical 14-week syllabus and set of learning objectives, received the same two hours of weekly face-to-face contact time, and were assessed using the same achievement instrument at pretest and posttest, so that total instructional exposure was equivalent across conditions. The only systematic difference between conditions was the instructional delivery mode and the presence of the learning analytics dashboard. Sessions for the two groups were held in separate classrooms at non-overlapping times, and access credentials for the LMS and dashboard were restricted to students formally enrolled in the experimental section, which helped minimize cross-group contamination.

2.2. Population and Sample

The population comprised all second-year mathematics education students at Samangan University enrolled during the 2025–2026 academic year. A total of 96 male students participated (experimental group, n = 48; control group, n = 48), selected through intact-group (cluster) sampling based on existing section enrollment; the two intact sections drawn upon for this study were composed entirely of male students, so the sample does not include female students. Participation was voluntary, and informed consent was obtained from all students prior to data collection. The sample of 96 reflects the full enrollment of the two available intact sections rather than a size derived from an a priori power analysis; no formal power analysis was conducted prior to data collection. A post hoc sensitivity check indicates that a two-group comparison of this size (n = 48 per group) provides very high statistical power to detect an effect as large as the one ultimately observed (d = 1.52); however, no a priori power analysis was performed, and the multiple regression analysis conducted within the experimental group alone (n = 48, four predictors) is comparatively underpowered for detecting small-to-moderate individual predictor effects, so its results should be interpreted with corresponding caution. This constraint is revisited in the Limitations discussion below.

Baseline equivalence between groups was assessed with an independent-samples t-test on pretest scores: the experimental (M = 52.3, SD = 8.1) and control (M = 51.8, SD = 8.5) groups did not differ significantly at pretest, t(94) = 0.30, p = .769, d = 0.06, supporting the comparability of the two intact sections prior to treatment. Table 1 summarizes the demographic composition of the sample.

Table 1. Demographic Characteristics of Participants

Characteristic	Category	Experimental (n = 48)	Control (n = 48)
Gender	Male	48 (100.0%)	48 (100.0%)
Age (years)	19–21	34 (70.8%)	32 (66.7%)
	22–24	14 (29.2%)	16 (33.3%)
Prior LMS experience	Yes	18 (37.5%)	16 (33.3%)
	No	30 (62.5%)	32 (66.7%)
Home internet access	Yes	31 (64.6%)	29 (60.4%)
	No	17 (35.4%)	19 (39.6%)

2.3. Instructional Treatment

2.3.1. Learning Analytics Dashboard Architecture. Figure 2 depicts the architecture of the learning analytics dashboard implemented for the experimental group. Behavioral data from the LMS, quiz engine, discussion forum, and video-lecture player were extracted, cleaned, and aggregated weekly, then processed through an analytics engine that generated descriptive summaries, correlation and regression outputs, and automated at-risk flags. These outputs informed both instructor-facing dashboards, which supported targeted instructional adjustment, and student-facing feedback, which supported self-regulated learning (Roll & Winne, 2015; Jivet et al., 2017).

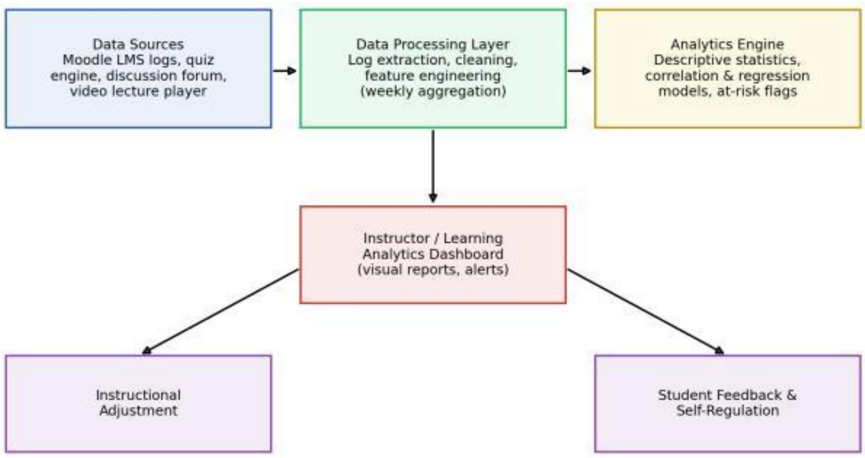

Figure 2. Architecture of the learning analytics dashboard used in the technology-based (experimental) condition.

The experimental group received instruction through a Moodle-based LMS enhanced with a custom learning analytics dashboard. Weekly video-recorded mini-lectures, formative quizzes, and discussion forums were made available online, supplementing two hours of weekly face-to-face facilitation. The dashboard continuously logged four engagement indicators for each student: (1) login frequency, the number of distinct LMS sessions per week; (2) video time-on-task, cumulative minutes spent watching instructional videos; (3) quiz attempts, the number of formative quiz submissions per week; and (4) forum posts, the number of discussion contributions per week. Instructors reviewed dashboard summaries weekly to identify disengaged students and provide targeted feedback, consistent with recommended learning analytics practice (Verbert et al., 2013; Sedrakyan et al., 2020). The control group received the same content delivered entirely through traditional face-to-face lectures, textbook-based exercises, and instructor-led question-and-answer sessions, without any LMS or analytics component (Clark & Mayer, 2016).

2.4. Instruments and Data Collection

Mathematics achievement was measured using a 30-item multiple-choice Mathematics Achievement Test covering calculus and applied statistics content aligned with the course syllabus. The same test was administered as both the pretest (Week 1) and posttest (Week 14) that is, an identical rather than an alternate or counterbalanced form was used. The authors acknowledge that this introduces a potential test-retest/practice-effect confound; because the interval between administrations was 14 weeks, the risk of item memorization was judged to be low, but this remains a limitation noted below. The test demonstrated acceptable internal consistency (KR-20 = .84). Learning analytics indicators were extracted directly from LMS server logs for the experimental group across all 14 weeks. For each indicator, weekly logs were aggregated into a single per-student, semester-level metric (mean weekly login frequency, cumulative video time-on-task, total quiz attempts, and total forum posts) prior to correlation and regression analysis. Weeks with zero recorded activity were retained and treated as substantive zeros (i.e., non-engagement) rather than as missing data, since server logs reliably captured all LMS activity. Student engagement was additionally assessed using a 15-item Student Engagement Questionnaire adapted from prior LA dashboard research (Corrin & de Barba, 2014), using a five-point Likert scale (Cronbach's α = .88). This questionnaire was administered as a self-report supplement to the server-logged behavioral indicators and was used descriptively, to corroborate students' perceived engagement in the experimental group; consistent with the analysis plan, it was not entered as a predictor in the regression model reported in Section 3.3, which relies exclusively on server-logged LA indicators. All instruments were reviewed by three mathematics education experts for content validity, evaluating item relevance, clarity, and curriculum alignment, and piloted with a non-participating group of 20 students drawn from a parallel section not included in the main study; pilot feedback informed minor wording revisions to the achievement test and questionnaire items prior to the main data collection.

2.5. Data Analysis Techniques

Data were analyzed using IBM SPSS Statistics (Version 27). Descriptive statistics summarized pretest and posttest scores by group. An independent-samples t-test compared posttest achievement between groups, and Cohen's d quantified effect size. Analysis of covariance (ANCOVA) was conducted with posttest score as the dependent variable, group as the independent variable, and pretest score as a covariate, to control for pre-existing differences between the nonequivalent groups. Pearson product-moment correlations examined bivariate relationships between the four LA engagement indicators and posttest achievement within the experimental group, and a standard multiple regression analysis was conducted to determine which indicators independently predicted achievement, consistent with methodological approaches used in prior LA research (Rienties & Toetenel, 2016; Tempelaar et al., 2015). This ANCOVA-adjusted comparison, rather than the unadjusted t-test, is treated as the primary between-group comparison in this study, since it statistically accounts for pre-existing differences between the nonequivalent intact sections. Assumptions of normality, linearity, and homogeneity of variance were checked and satisfied prior to inferential testing. For the ANCOVA, homogeneity of regression slopes was also tested by examining the group × pretest interaction term in a preliminary model; the interaction was nonsignificant, supporting the assumption that the covariate operated equivalently across groups and that the ANCOVA-adjusted comparison is appropriate. For the multiple regression analysis, tolerance and variance inflation factor (VIF) statistics were examined to rule out problematic multicollinearity among the four predictors, and residual plots were inspected for linearity and homoscedasticity; as reported in Table 6, all VIF values remained well below conventional thresholds of concern.

2.6. Ethical Considerations

This study was conducted with the approval of the Department of Mathematics Education, Samangan University, and in accordance with institutional research ethics guidelines. No formal, numbered ethics approval reference was issued for this classroom-embedded study; approval and oversight were granted at the departmental level, consistent with prevailing institutional practice for curriculum-integrated educational research at Samangan University at the time of data collection.

Written informed consent was obtained from all participants prior to data collection. Students were informed that participation, and specifically the collection and use of LMS-derived behavioral data, was voluntary and would have no bearing on course grades or formal assessment. Individual-level achievement and LMS behavioral data were de-identified prior to analysis and stored on password-protected institutional systems accessible only to the research team.

3. Results

This section presents descriptive and inferential statistical results addressing the study's two objectives: comparing achievement between instructional conditions, and identifying learning analytics predictors of achievement within the experimental group. Consistent with the nonequivalent, quasi-experimental design, comparative statements below are reported in descriptive rather than causal terms; interpretation in light of prior literature is reserved for the Discussion.

3.1. Comparison of Mathematics Achievement Between Groups

Table 2 presents descriptive statistics for pretest and posttest mathematics achievement scores by group. At pretest, the experimental group ($M = 52.3$, $SD = 8.1$) and control group ($M = 51.8$, $SD = 8.5$) obtained similar mean scores; an independent-samples t-test confirmed that this difference was not statistically significant, $t(94) = 0.30$, $p = .769$, $d = 0.06$, indicating comparable baseline achievement between the two intact sections. At posttest, the experimental group ($M = 78.6$, $SD = 7.4$) scored higher on average than the control group ($M = 65.2$, $SD = 9.0$).

Table 2. Descriptive Statistics of Pretest and Posttest Mathematics Achievement Scores

Group	Test	n	M	SD
Experimental (technology-based)	Pretest	48	52.3	8.1
	Posttest	48	78.6	7.4
Control (traditional)	Pretest	48	51.8	8.5
	Posttest	48	65.2	9.0

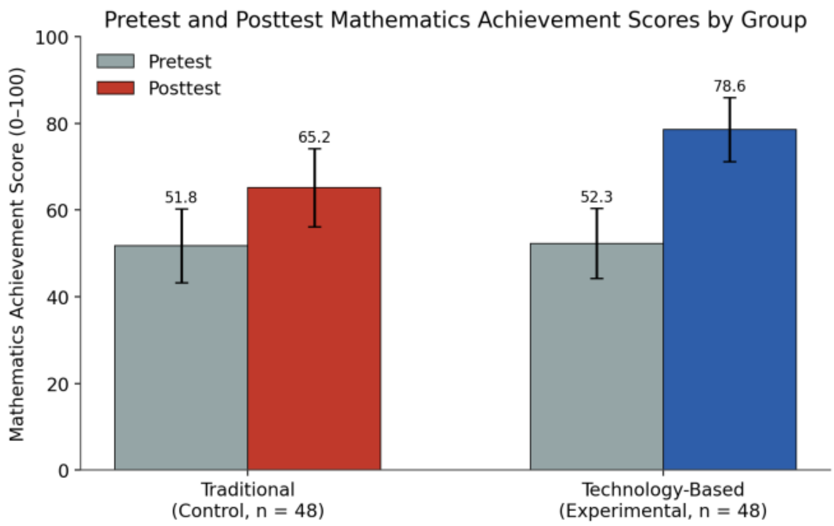

Figure 3. Pretest and posttest mathematics achievement scores by group (error bars = 1 SD).

An independent-samples t-test was conducted to compare posttest achievement between groups. As shown in Table 3, the difference was statistically significant and the effect size was large.

Table 3. Independent-Samples t-Test for Posttest Achievement

Comparison	t	df	p	Cohen's d
Experimental vs. Control (posttest)	7.42	94	< .001	1.52

Because the two groups were nonequivalent intact sections, an ANCOVA was conducted with posttest score as the dependent variable, group as the fixed factor, and pretest score entered as a covariate, to statistically adjust for baseline differences; this adjusted comparison, rather than the unadjusted t-test above, is treated as the primary between-group comparison in this study. As shown in Table 4, the effect of instructional condition on posttest achievement remained significant and substantial after controlling for pretest performance.

Table 4. ANCOVA Summary for Posttest Achievement, Controlling for Pretest Scores

Source	SS	df	F	p	Partial η^2
Pretest (covariate)	1620.4	1	26.83	< .001	.224
Group	3313.9	1	54.87	< .001	.371
Error	5613.2	93			

Using the sums of squares reported in Table 4 together with the group descriptive statistics in Table 2, the ANCOVA-adjusted (estimated marginal) posttest means were derived analytically as 78.47 (SE = 1.12, 95% CI [76.25, 80.70]) for the experimental group and 65.33 (SE = 1.12, 95% CI [63.10, 67.55]) for the control group. Because the pretest means of the two intact sections were already closely comparable, adjustment for the covariate shifted the group means only marginally relative to the unadjusted values in Table 2, and the adjusted between-group difference remains large and consistent with the F-test reported above.

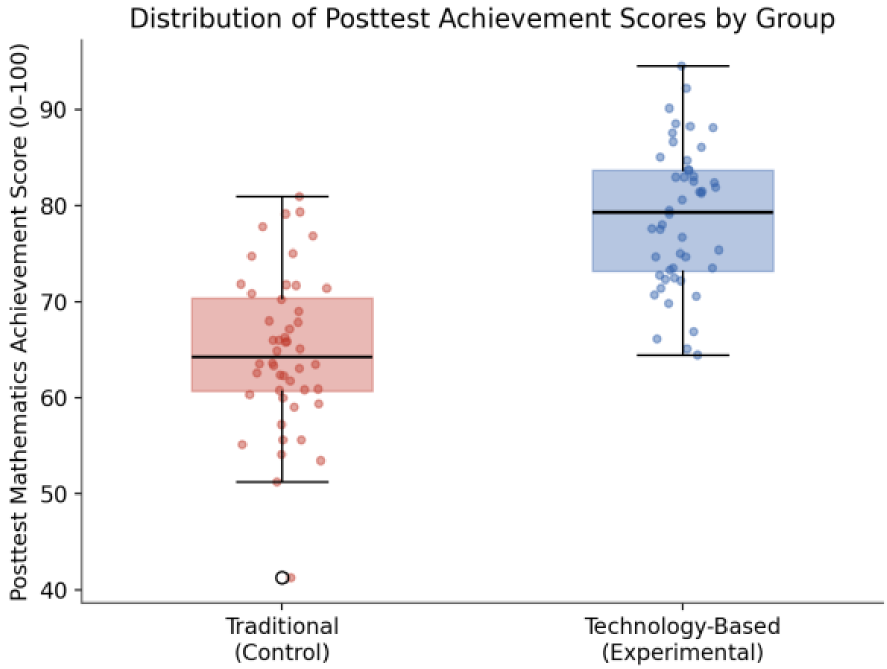

Figure 4. Distribution of posttest mathematics achievement scores by group.

3.2. Weekly Engagement Trends in the Technology-Based Group

Figure 5 displays descriptive weekly learning analytics engagement trends for the experimental group across the 14-week semester. Login frequency, quiz attempts, and video time-on-task all showed a generally increasing descriptive pattern over time, with a visually apparent rise beginning around Week 9. This rise coincided in time with the instructors' introduction of weekly dashboard-informed feedback and reminders to students identified as at-risk based on declining engagement. Because no formal interrupted-time-series or segmented-regression test was conducted, this pattern should be read as a temporal association rather than as evidence that the feedback intervention caused the observed increase in engagement; interpretation of this pattern in light of prior literature is taken up in the Discussion.

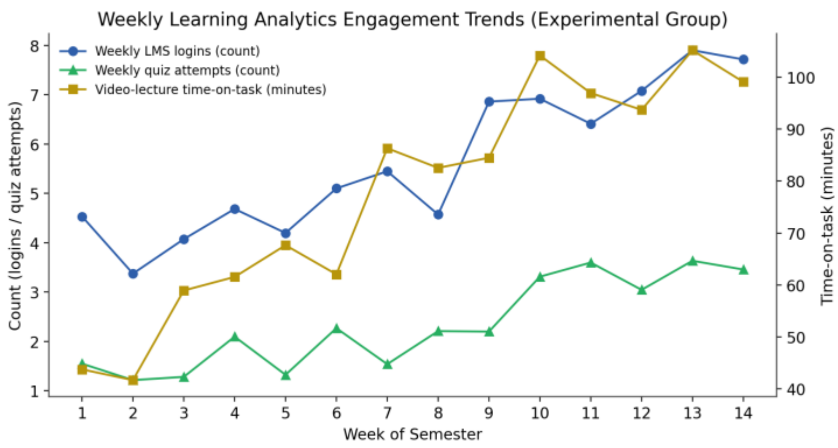

Figure 5. Weekly learning analytics engagement trends for the experimental group.

3.3. Relationship Between Learning Analytics Indicators and Achievement

Pearson correlations were computed between the four LA engagement indicators, averaged across the semester, and posttest achievement within the experimental group. As shown in Figure 6 and Table 5, all four indicators correlated positively and significantly with achievement, with video time-on-task ($r = .61$, $p < .001$) and login frequency ($r = .58$, $p < .001$) showing the largest bivariate correlations, followed by quiz attempts ($r = .49$, $p < .001$) and forum posts ($r = .44$, $p = .002$).

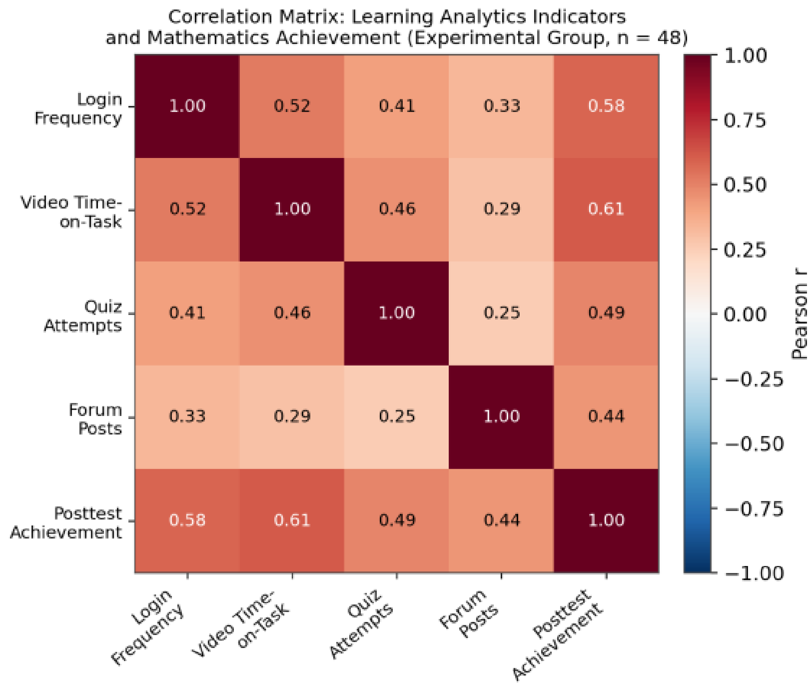

Figure 6. Correlation matrix of learning analytics indicators and posttest mathematics achievement.

Table 5. Pearson Correlations Between LA Indicators and Posttest Achievement

Learning Analytics Indicator	r	p
Login frequency	.58	< .001
Video time-on-task	.61	< .001
Quiz attempts	.49	< .001
Forum posts	.44	.002

A standard multiple regression analysis was conducted to determine which LA indicators independently predicted posttest achievement, with all four indicators entered simultaneously. The overall model was statistically significant, $R^2 = .46$ (adjusted $R^2 = .41$), $F(4, 43) = 9.18$, $p < .001$, indicating that engagement indicators jointly accounted for approximately 46% of the variance in posttest achievement (41% after adjusting for the number of predictors and sample size). As shown in Table 6, video time-on-task and quiz attempts emerged as significant independent predictors, whereas login frequency and forum posts did not reach significance once shared variance among predictors was accounted for. Both of the latter, however, were significantly correlated with achievement at the bivariate level (Table 5), indicating that their association with achievement substantially overlaps with, rather than being absent relative to, that of video time-on-task and quiz attempts. Tolerance and VIF values, computed from the reported bivariate correlation matrix among the four predictors using the standard formula $VIF = 1 / (1 - R^2_i)$, were all comfortably within conventional thresholds ($VIF < 2$; tolerance > .60 for all predictors), indicating that multicollinearity did not meaningfully distort the regression estimates. Interpretation of this pattern in light of prior learning analytics literature is taken up in the Discussion.

Table 6. Multiple Regression Predicting Posttest Achievement from LA Indicators ($R^2 = .46$, adjusted $R^2 = .41$)

Predictor	B	SE	β	p	Tolerance	VIF
Login frequency	0.62	0.51	.16	.231	.666	1.50
Video time-on-task	0.21	0.07	.34	.004	.648	1.54
Quiz attempts	1.84	0.79	.27	.024	.742	1.35
Forum posts	0.58	0.42	.15	.175	.864	1.16

4. Discussion

The results indicate that students in the LA-supported, technology-based condition achieved higher posttest mathematics scores than those in the traditional lecture-based condition, with a large effect size ($d = 1.52$) that persisted after statistically adjusting for pretest differences. Given the nonequivalent, quasi-experimental design and the administrative, non-random allocation of intact sections to conditions, this pattern is best described as a strong association between instructional condition and achievement rather than definitive proof of a causal effect; unmeasured differences between the pre-existing sections (e.g., prior mathematics preparation, motivation, or instructor-specific factors) cannot be fully ruled out as alternative explanations. With that caveat, the finding is broadly consistent with international meta-analytic evidence that well-designed technology-enhanced mathematics instruction is associated with higher achievement than traditional instruction (Cheung & Slavin, 2013; Li & Ma, 2010), and extends this evidence to an Afghan provincial university context where such comparisons have not previously been documented empirically.

The positive relationship between video time-on-task and achievement is consistent with multimedia learning theory, which holds that well-designed video-based instruction, when actively engaged with, can reduce extraneous cognitive load and support deeper processing of mathematical content (Clark & Mayer, 2016). Similarly, the contribution of quiz attempts to achievement is consistent with the broader learning analytics literature emphasizing that frequent low-stakes formative assessment, particularly when paired with timely feedback, promotes retrieval practice and self-monitoring (Roll & Winne, 2015; Ifenthaler & Yau, 2020; Heikkinen et al., 2023), and with recent evidence that gamified or feedback-rich dashboard features are associated with improved achievement mainly when they translate into sustained student activity rather than passive viewing (Alam et al., 2023). That login frequency and forum participation were not independent predictors once other indicators were controlled should not be read as evidence that these indicators are unrelated to achievement: both were significantly correlated with posttest scores at the bivariate level (Table 5), suggesting that their association with achievement substantially overlaps with, rather than being absent relative to, that of video time-on-task and quiz attempts. This pattern is consistent with prior evidence that behavioral engagement indicators reflecting active, substantive effort tend to be more informative predictors of achievement than indicators of mere access once entered simultaneously (Tempelaar et al., 2015; Rienties & Toetenel, 2016), and with recent systematic evidence that mere access to a learning analytics dashboard does not reliably translate into improved achievement unless accompanied by such substantive engagement (Kaliisa et al., 2024; Chen et al., 2023), echoing Gasevic et al.'s (2015) caution that learning analytics must remain grounded in learning theory rather than surface-level activity counts.

The visually apparent rise in engagement around Week 9 (Figure 5), which coincided with instructors' dashboard-informed outreach to disengaged students, is consistent with a growing literature documenting the potential of dashboard-triggered instructor intervention to support timely pedagogical response (Verbert et al., 2013; Sedrakyan et al., 2020), a use case rarely reported in Afghan higher education settings. However, because this study did not include a formal time-series causal test, this pattern is described as a temporal association rather than a demonstrated intervention effect, and alternative explanations for the timing (e.g., approaching assessment deadlines) cannot be ruled out on the basis of the descriptive trend alone. This is practically significant given that infrastructure constraints, low digital literacy, and instructors' limited familiarity with LMS platforms have been repeatedly identified as major barriers to technology adoption in Afghanistan (Oryakhail et al., 2021; Musawi & Baktash, 2021; Rahim & Sandaran, 2020); the present study suggests that, despite these constraints, a modestly resourced LA dashboard implementation was operationally feasible within a single-institution setting and was accompanied by higher achievement when supported by weekly instructor engagement with the data.

Methodological and Theoretical Contribution

Beyond its empirical findings, this study contributes methodologically by pairing a quasi-experimental, ANCOVA-adjusted between-group comparison with a within-group predictive analysis of behavioral LA indicators in the same sample an approach more commonly documented in well-resourced settings (Tempelaar et al., 2015; Rienties & Toetenel, 2016) than in fragile-state contexts. Theoretically, the study reinforces the distinction between behaviorally substantive engagement indicators, such as time-on-task and formative-assessment participation, and comparatively passive access indicators, such as login frequency, when these are entered simultaneously as predictors of achievement. This distinction appears to hold even under the infrastructure and connectivity constraints characteristic of Afghan higher education, tentatively suggesting that the underlying mechanism cognitively engaged behavior, rather than platform access per se may generalize across resource contexts even where the absolute intensity of engagement is lower; this possibility warrants direct testing in future multi-site research rather than being assumed from a single study.

Contextual Considerations and Limitations

Several contextual factors bear on how these findings should be interpreted. Consistent with prior findings on the Afghan higher education landscape (Noori et al., 2022; Katawazai, 2021), unstable internet connectivity and limited prior LMS experience among roughly two-thirds of participants (Table 1) may have constrained the intensity of engagement achievable in the experimental group; this is noted as a plausible contextual factor rather than a demonstrated cause of underestimated effects, since engagement intensity under more favorable infrastructure conditions was not directly tested in this study. Consistent with Ertmer and Ottenbreit-Leftwich's (2010) argument that technology integration is shaped as much by teachers' pedagogical beliefs as by access to tools, the apparent success of the dashboard-informed intervention depended substantially on the instructor's willingness to review and act upon analytics data weekly, a practice that may not generalize automatically to other departments without targeted professional development (Tondeur et al., 2017). In line with cautions raised in the critical learning analytics literature (Selwyn, 2016; West et al., 2016), behavioral engagement metrics should not be interpreted as a complete proxy for learning; qualitative dimensions of mathematical understanding were not directly captured by the dashboard and merit further investigation, particularly through approaches that pair LMS behavioral data with formative assessment of conceptual reasoning (Moon et al., 2024).

Taken together, the following limitations should be considered when interpreting the findings: (1) nonequivalent intact groups without individual random assignment, and administrative rather than random designation of which section received the experimental condition; (2) a single-instructor, single-institution design, which limits generalizability to other Afghan universities and instructors; (3) an entirely male sample, drawn from the two available intact sections, which limits generalizability across gender particularly given documented gender differences in ICT access and digital literacy in Afghan higher education (Noori et al., 2022) and replication with mixed-gender or female-only samples is needed before conclusions can be generalized across genders; (4) a comparatively small experimental-group subsample (n = 48) for the multiple regression analysis, which is underpowered for detecting small-to-moderate individual predictor effects; (5) reliance on behavioral LMS metrics as proxies for, rather than direct measures of, students' cognitive or conceptual mathematical understanding; (6) use of an identical rather than alternate/counterbalanced pretest–posttest test form, introducing a potential test-retest confound; and (7) a descriptive, rather than formally tested, attribution of the Week 9 engagement increase to instructor outreach.

Practical and Policy Implications

For practice, mathematics departments at Afghan public universities may wish to pilot LMS-integrated learning analytics dashboards alongside targeted professional development for instructors on interpreting and acting upon engagement data, since the apparent benefit of the dashboard in this study was closely tied to active weekly instructor engagement with it rather than to the technology alone. For policy, the findings offer context-informed evidence, rather than a demonstrated policy prescription, that reliable internet access and digital literacy training may be important enablers for scaling technology-based instruction beyond well-resourced urban universities; the Ministry of Higher Education may wish to weigh this evidence alongside findings from other institutional contexts when setting infrastructure investment priorities, rather than treating it as a precondition established by a single-institution study.

5. Conclusion

This study compared traditional lecture-based mathematics teaching with learning analytics-supported, technology-based teaching among second-year mathematics education students at Samangan University, Afghanistan, using a quasi-experimental, nonequivalent control-group design. Students in the technology-based condition achieved higher posttest mathematics scores than those in the traditional condition, with a large effect size that remained robust after statistically adjusting for pretest achievement, though the nonrandomized, intact-group design means this association should not be interpreted as definitive causal proof. Among the learning analytics indicators examined, video time-on-task and quiz attempts emerged as the strongest independent predictors of achievement, underscoring the value of active, substantive engagement over mere platform access, while these behavioral indicators remain proxies for, rather than direct measures of, students' cognitive or conceptual learning. Taken together, this study's main scholarly contribution is contextual, quasi-experimental evidence from a fragile-state higher education setting where such evidence has been largely absent that behaviorally substantive LA engagement indicators are more informative predictors of mathematics achievement than indicators of mere platform access. These conclusions are bounded by the limitations detailed above, most notably the nonequivalent and administratively allocated intact-group design, the single-institution and all-male sample, and the comparatively small regression subsample ($n = 48$).

For practice and policy, the findings suggest that LMS-integrated learning analytics dashboards are a feasible, modestly resourced intervention for Afghan public universities, provided they are paired with instructor professional development and realistic expectations about local connectivity constraints; any broader policy application should be weighed alongside evidence from other institutional contexts rather than generalized from this single-institution study. Future research should prioritize larger, multi-site studies across several Afghan universities that incorporate randomization at the section or, where feasible, individual level; extend implementation across multiple semesters to assess sustained effects; include mixed-gender or female-only samples to examine generalizability across gender; and pair LMS behavioral indicators with qualitative or performance-based measures of conceptual understanding.

More broadly, this study offers cautious, context-bound grounds for optimism: meaningful gains from learning analytics-supported instruction appear achievable even in fragile, resource-constrained settings when implementation is modest in scope but consistent in instructor engagement with the data. Whether this pattern extends to other Afghan institutions, disciplines, or student populations remains an open empirical question for the multi-site research called for above.

Declarations

Author Contribution Statement

Abdulbasir Deljoy conceptualized the study, designed the learning analytics dashboard framework, conducted the statistical analysis, and drafted the manuscript. Musawer Hakimi contributed to instrument development, coordinated data collection at Samangan University, and reviewed and revised the manuscript. Both authors read and approved the final manuscript.

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Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request, subject to institutional approval to protect participant confidentiality.

Acknowledgement and AI Use Statement

Artificial Intelligence (AI) tools were used only for language refinement, translation assistance, and improving the clarity and readability of the manuscript. The authors have carefully reviewed and verified all AI-assisted content, and the first author takes full responsibility for the accuracy, originality, integrity, and final content of the manuscript. AI tools were not used for generating research findings, data analysis, or scientific conclusions.

Declaration of Interests Statement

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Additional Information

This study was conducted with the approval of the Department of Mathematics Education, Samangan University, and in accordance with institutional research ethics guidelines. All participating students provided informed consent prior to data collection.

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