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PAPER

Mobile Learning Analytics for Data Science-Driven Cognitive Skill Development in Computer Science Engineering

Srividhya S.[1] (✉),
Ranjani M.[1],
Rajesh Kumar K.[2],
Praveenkumar R.[3],
Ramakrishnan P.[4]

[1]SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India

[2]SRM Institute of Science and Technology, Tiruchirappalli, Tamil Nadu, India

[3]Nandha Engineering College, Erode, Tamil Nadu, India

[4]M. Kumarasamy College of Engineering, Karur, Tamil Nadu, India

srividhs1@srmist.edu.in

ABSTRACT

The current CSE curriculum must cater to the rising interest in data science competencies, which requires teaching and learning models that structurally strengthen higher-order cognitive skills. In this paper, we propose a data science–orientated mobile learning analytics (MLA) framework that aims to support undergraduate CSE students in developing critical thinking, problem-solving, analytical reasoning, self-regulated learning, and knowledge retention skills through empirical validation. Using a purpose-built mobile learning platform, the 16-week quasi-experimental study engaged 120 undergraduate students (experimental group: n = 62; control group: n = 58) and extracted multimodal learner data including interaction logs, formative assessment records, behavioural engagement metrics and self-regulatory survey information. Techniques from learning analytics, including statistical inference and machine learning–based predictive modelling, were used to analyse learner trajectories and identify at-risk students. Independent-samples t-tests showed statistically significant improvements in the experimental group on all five dimensions of cognition ($p < .001$), with Cohen's d effect sizes between 0.97 and 1.19 reflecting large practical significance. A gradient boosting classifier based on XGBoost attained a learning accuracy of 89.2% (AUC–ROC = 0.931) in identifying at-risk learners and allowed for timely personalised interventions, resulting in an early intervention success rate of 72.7% among flagged learners who managed to cross above the risk threshold by mid-semester. This paper proposes an MLA framework to create a scalable pedagogy that provides coherence between Bloom's revised taxonomy, Zimmermann's model of self-regulated learning (SRL) and the SAMR model. The findings substantively advance the empirical knowledge base for data science–enabled engineering education and provide evidence-based guidance to inform curriculum designers and educators who implement learner-centred, analytically augmented pedagogical strategies in data-intensive computing programmes.

KEYWORDS

mobile learning analytics (MLA), cognitive skill development, data science in education, learning analytics, educational data mining, XGBoost, self-regulated learning (SRL), at-risk prediction, engineering education, quasi-experimental design

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1 INTRODUCTION

Surveys by the World Economic Forum [1] and leading technology employers have uniformly reported a growing gap between the analytical abilities that entry-level data science incumbents are expected to possess and the cognitive skill profiles produced by traditional undergraduate CSE curricula. Specifically, in the meta-analysis of 197 experts who provided qualitative data on gaps between education and workforce readiness, employers described a "triple deficit," including [viz.]: (i) a lack of ability to critically evaluate the validity and limitations of data-driven models; (ii) poor capacity for complex, multi-step problem-solving in conditions of ambiguity; and (iii) deficits in metacognitive self-regulation (needed to navigate rapidly advancing technical environments without constant external correction) [2]. These competency gaps cannot simply be attributed to deficiencies in curricular content but rather stem from a deeper misalignment between dominant organisational modalities for instruction in engineering education and the cognitive demand of data-intensive computing practice. Traditional lecture-centred instruction defined by passive transmission of knowledge, infrequent and summative assessments, and the physical and temporal constraints of scheduled classroom hours is thus structurally ill-suited to generating the iterative, reflective, and self-directed cognitive process that defines expert practice [3]. Mobile platforms decouple learning engagement from the limitations of fixed-schedule classroom instruction, facilitating continual, contextually embedded interaction with learning content that draws on principles of cognitive science as optimal for long-term knowledge acquisition and higher-order skill development [4], including distributed practice and spaced retrieval. However, adding mobile learning platforms without further analysis of the data that they generate from learners adds a minimal level of pedagogical value. Over a decade ago, learning analytics (LA) transitioned from educational data mining to a matured applied discipline capable of supporting real-time, individualised instructional decision-making at scale [5]. LA methods permit the transformation of raw interaction data, clickstreams, assessment histories, collaborative patterns, and temporal engagement metrics into diagnostic insights about individual learner trajectories; predictive models of academic risk; and prescriptive recommendations for personalised interventions. When combined with a mobile learning platform, LA creates a closed-loop instructional ecosystem where each learner's engagement continuously informs the optimisation of their learning experience, something traditional instruction is inherently incapable of doing [6].

1.1 Research objectives

This study pursues four primary objectives:

1. To design a theoretically grounded, data science-driven mobile learning analytics (MLA) framework integrating mobile delivery, multimodal data capture, learning analytics processing, and adaptive personalised intervention for undergraduate CSE education.
2. To empirically evaluate the effectiveness of the MLA framework in fostering cognitive skill development specifically, critical thinking, problem solving, analytical reasoning, self-regulated learning, and knowledge retention—through a controlled quasi-experimental study.

3. To construct, compare, and validate machine learning–based predictive models trained on multimodal learner analytics data for the early identification of at-risk learners.
4. To derive and articulate evidence-based recommendations for curriculum designers, technology developers, and educators seeking to implement analytically augmented, learner-centred instructional strategies in data science-oriented engineering programmes.

1.2 Research questions

This study is driven by the following research questions:

RQ1: Is the MLA framework significantly more effective in improving cognitive skill development among undergraduate CSE students than traditional lecture-based instruction?

RQ2: What is the educational effect [7] of the MLA framework on each measured cognitive dimension (critical thinking, problem-solving, analytical reasoning, SRL and knowledge retention)?

RQ3: To what extent can machine learning-based predictive models that are trained on multimodal MLA data correctly classify at-risk learners, and which learner attributes are most diagnostically informative?

RQ4: What practical implications does the MLA framework provide for data science-driven CSE curricula and technology-enhanced learning environments?

2 LITERATURE REVIEW

2.1 Cognitive skill development in engineering education

The last two decades have seen significant epistemological recasting of engineering education, fuelled by the emergence of accreditation mechanisms—primarily ABET (Accreditation Board for Engineering and Technology) and NBA (National Board of Accreditation) in India—which explicitly require the nurturing of higher-order thinking abilities beyond just assimilation of procedural knowledge [10]. Bloom's original taxonomy has been widely adopted in the engineering education community, but a differentiation amongst cognitive skills is most recalibrated by Anderson and Krathwohl [2], who provided an updated version of Bloom's original classroom-level structure whereby six levels were created which classified lower-order cognitive competencies (remember, understand, apply) from those that are higher-order when seen in relation to professional engineering practice with many competency model constructs (analyse, evaluate, and create). Self-regulated learning (SRL) in the shape of goal-setting, strategic planning, self-monitoring, and metacognitive reflection has been recognised as a significant mediating variable for academic achievement across such instructional modalities, especially so in technology-rich learning environments where learner autonomy is greatly augmented [12–13].

2.2 Mobile learning in higher education

With the rise of the smartphone as a personal, portable device found in almost every pocket, the information available to learners has changed dramatically and opened up new mobile learning. Mobile-supported learning has been found effective relative to non-mobile conditions (d = 0.52; Chao et al., 2016 meta-analysis of 110 study effect sizes) most globally across STEM disciplines in which affording pedagogical leverage through interactive simulations and real-time data collection is maximised. Mobile technologies embody unique instructional affordances specific to their functionality that correspond well with CSE education, such as immediacy in access to reference materials and computational tools, blended delivery of multimodal content integrating video, interactive simulations, and adaptive assessment; cognitive scaffolding through push notification–mediated communication supporting learners between times spent on formal learning; peer collaboration features enabling asynchronous co-creation of knowledge; and geolocation capabilities that enable contextually anchored real-world problem solving. However, critically, the pedagogic value of these affordances is dependent on intentional instructional design that preserves the alignment between mobile activities and explicit learning outcomes while offering systematic means to track and support individual learner progress, a demand which makes it essential to embed learning analytics in mobile learning architectures [16]. Long-standing barriers to mobile learning implementation include inequities and inequalities in digital equity and access, motivational issues related to the co-presence of affordances for distraction on personal devices, an absence of adaptive instructional mechanisms in the majority of commercially available mobile learning platforms, as well as a general lack of theoretical framing guiding many mobile learning implementations. However, these pressures highlight the necessity of a theoretically grounded design process bolstered by analytics.

3 THEORETICAL FRAMEWORK

3.1 Bloom's revised taxonomy: cognitive scaffolding

Anderson and Krathwohl's [2] revision of Bloom's original taxonomy of educational objectives provides the primary cognitive architecture for the instructional sequencing and assessment design of the MLA framework. The taxonomy's structure progresses hierarchically through six levels of cognitive functioning: remembering, understanding, applying, analysing, evaluating and creating, which in turn provides a basis for planning and sequencing mobile learning modules; calibrating the cognitive demand of embedded assessments; and interpreting individual learner performance trajectories from within the analytics engine. The 16-week intervention is operationalised into four phases of four weekly sessions each at incrementally higher cognitive levels. Weeks 1–4 focus on remembering and understanding foundational objectives through conceptual video modules with recognition-based quizzing. Weeks 5–8 activate application-level competences with engaging sets of interactive problems that require both the implementation of algorithms for data processing and interpretation of statistical outputs. Weeks 9–12 progress to analysis and evaluation via case-based exercises in which learners must critique design decisions for a model, as well as compare competing analytical approaches. Weeks 13–16 address creation-level Learning Objectives via capstone, open-ended projects where learners create and present original data science pipelines. This sequencing aligned with a taxonomy ensures that cognitive development is scaffolded over time as opposed to being left to incidentally come from exposure to unstructured content.

3.2 TAM and SAMR framework

The learner perceptions of the perceived usefulness and ease of use associated with the mobile platform are also evaluated, according to Davis TAM (Technology acceptance model), which advocates that these core constructs have shown to be the most reliable determinants of users voluntarily adopting a technology and continuing to use it over time. The MLA framework was designed with usability principles consistent with those described by the TAM, including simplicity of interface and processes; tangible feedback on learner actions (tangible in this case does not imply physical but rather accessible); clear communication about the actual relevance of analytical data to learning; and a flow of assessment data that minimises friction. A widely accepted framework for characterising these levels of transformation is the Substitution–Augmentation–Modification–Redefinition (SAMR) model, which can be applied to the MLA framework.

4 PROPOSED MLA FRAMEWORK

4.1 Conceptual architecture overview

We propose what we refer to as the MLA framework, a multilayer, close-loop instructional architecture consisting of four key functionally distinct but tightly integrated operational layers that perform high-level and abstract functions: (i) the Mobile Delivery Layer facilitating the learner-facing pedagogical interface; (ii) the Multimodal Data Capture Layer responsible for systematic capture of heterogeneous student data streams; (iii) the Learning Analytics Engine—a layer performing actual computation whereby raw data is transformed into diagnostic, predictive and prescriptive intelligence; and (iv) the Adaptive Intervention Layer where analytics output is translated into targeted, personalised instructional interventions at both learner and instructor levels. The interactivity is layered, with each layer working in continuous feedback with adjacent layers to create a dynamic, self-correcting instructional ecosystem that evolves over time according to the near real-time individual learner trajectories.

4.2 Mobile delivery layer

The Mobile Delivery Layer represents the primary instruction interface by which learners experience course content, formative assessments and collaboration. In this layer, we design a cross-platform (iOS 13.0+ and Android 9.0+) mobile application using the React Native framework which can work on all kinds of devices and OSes. The app architecture is very much hierarchical, with a modular content model which spans the four pedagogical stages of the Bloom's taxonomy-aligned curriculum. Modes of content delivery in the app include (1) short instructional videos (5–12 minutes, following principles for cognitive load-informed segmentation), (2) interactive data science problem sets with embedded scaffolding prompts, (3) peer discussion threads with structured argumentation protocols, (4) scenario-based case studies based on real-world CSE data science applications (e.g., data pipeline design, algorithm complexity analysis, model validation and interpretability challenges), and (5) spaced-repetition flashcard modules targeting retention of foundational concepts. Formative assessments are provided as adaptive quizzes tailored to the learner's level of knowledge at any given moment using an Item Response Theory (IRT) scoring model with immediate automated feedback that describes not just correctness but explanatory scaffolding that relates incorrect responses to specific conceptual gaps identifiable in the history of the learner's interactions.

4.3 Multimodal data capture layer

These five categories of learner-generated data, if harvested systematically, make up the empirical substrate for all downstream analytics operations and are made available by the Multimodal Data Capture Layer. These categories of data include: (1) behavioural interaction logs that track all application touchpoints such as screen transitions, content play/pause events, assessment item responses, and navigation patterns at 5-second sampling granularity; (2) temporal engagement measures such as session time, active time-on-task, inter-session gaps and login frequency; (3) formative learning path performance records featuring item-level response data derived from 16 weekly quiz cycles to enable fine-grained cognitive diagnostic analysis rather than aggregative score monitoring; (4) social collaboration metrics based on peer discussion forum participation indexed as post frequency; response quality ratings (peer-evaluated on a 4-point rubric); co-authorship patterns in collaborative problem-solving tasks; and network centrality indices computed from student-to-student interaction graphs; and (5) self-report SRL instruments captured by way of in-application Likert-scale surveys administered at weeks 4, 8,12, and 16. Data is always transmitted over encrypted REST APIs (with TLS 1.3 encryption) to the cloud-hosted and AES-256-encrypted at rest data warehouse (AWS RDS), which ingests it into a streaming data pipeline (Apache Kafka) for real-time processing. Such a complete data governance protocol, from the requirement of field-level anonymisation at ingestion to role-based access control and automatic audit logging, ensures compliance with institutional data protection policies and participant privacy assurances.

4.4 Learning analytics engine

The learning analytics Eegine constitutes the data science core of the MLA framework, operationalising a three-stage computational pipeline: data preprocessing, feature engineering, and predictive model deployment. In the preprocessing stage, raw event data are normalised (min-max normalisation for continuous features), missing values imputed using k-nearest neighbour interpolation ($k = 5$), and outliers detected and flagged using the interquartile range (IQR) method. The preprocessing stage ensures analytical data quality before downstream feature construction. The feature engineering stage constructs 28 learner features from pre-processed event streams. Features span four categories: clickstream-derived behavioural features (e.g., login frequency, time on task per session, and navigation depth), performance-derived cognitive features (e.g., assessment trajectory slope, rolling average score, and item difficulty distribution), engagement composite features (e.g., engagement velocity, module completion rate, and notification response rate), and social-collaborative features (e.g., forum participation index, peer interaction centrality, and co-authorship count). The feature set was iteratively refined through forward feature selection experiments, retaining features with statistically significant univariate associations with at-risk status (χ^2 tests, all $p < .01$) and non-redundant information content (variance inflation factor < 5.0).

5 RESEARCH METHODOLOGY

5.1 Research design

The study adopted a quasi-experimental pre- and post-test non-equivalent control group (CG) design as the main research design. Despite this limitation—which is often openly noted within the literature on pedagogical (schooling) interventions in educational settings and managed methodologically in terms of strictly validating homogeneity of baseline characteristics rather than using randomisation—we chose this design due to institutional scheduling constraints that precluded alternative methods offering a full assignment of students to experimental conditions. During the 16-week semester, the experimental (EG) and CG were instead taught by the proposed MLA framework and conventional lecture-based teaching with standard learning management system (LMS) resources providing static reading materials and end-of-unit assessments, respectively.

Both groups were taught the same curriculum content module on Introduction to Data Science for Computer Science Engineering, which included coverage of data pre-processing, exploratory data analysis, statistical inference, supervised learning (SL), unsupervised learning (UL) and model evaluation, ensuring equivalent content across conditions at the crux of implicating instructional modality differential as a treatment variable. A sole faculty member taught both cohorts to control for instructor effect as a confounding factor. The groups were also comparable in baseline cognitive skills prior to intervention, as evident from pre-test score comparisons which showed no statistically significant difference.

5.2 Participants and sampling

The sample comprised 120 (19–22 years old) second-year Computer Science and Engineering undergraduates at an Indian private technical university for the academic year 2023–2024. Purposive sampling was used to only include participants from sections directly taught by the same faculty member, thereby reducing extant instructor effect confounds. The EG ($n = 62$) and CG ($n = 58$) assignment was done according to intact class section boundaries, which is a common quasi-experimental practice when randomisation is not feasible. Inclusion criteria were (a) owning a personal smartphone running Android 9.0+ or iOS 13.0+, (b) having at least a Cumulative Grade Point Average (CGPA) of 6.0 on a scale of [1–10], (c) reliable access to the internet every day, and (d) providing written consent for participation in data collection. Those with >20% absence on pre-registered sessions (EG: 2 students; CG: 1 student) were excluded from final analysis, securing total analytical sample at $N = 117$. Independent-samples t-tests confirmed no statistically significant between-group differences in age ($t(118) = 0.94$, $p = .350$) or prior CGPA ($t(118) = 0.24$, $p = .810$). Chi-square tests confirmed distributional equivalence in gender ($\chi^2(1) = 0.11$, $p = .739$), prior ML/DS course exposure ($\chi^2(1) = 0.01$, $p = .921$), and prior LMS usage patterns ($\chi^2(1) = 0.01$, $p = .906$), establishing robust baseline equivalence across all measured participant characteristics.

5.3 Simulation and experimental parameter configuration

Our operationalisation of the MLA framework involved a rigorous definition specification phase to encompass the various experimental and simulation parameters that governed the mobile learning environment, data-capturing infrastructure, assessment design and predictive modelling pipeline. The detailed parameter configuration can be seen in Table 1.

Table 1. Simulation and experimental parameter configuration with justifications

Parameter	Value/Range	Unit	Justification/Source
Study Duration	16	Weeks	Standard academic semester (Indian UG engineering)
Total Sample Size	120	Students	Power analysis: $\alpha = 0.05$, power = 0.80, $d = 0.5 \rightarrow n \geq 102$
Experimental Group	62	Students	Intact class; randomly selected from cohort
Control Group	58	Students	Intact class; conventional lecture instruction
Mobile Sessions per Week	3	Sessions	Aligned with 3-credit course contact hours
Session Duration	20–45	Min/session	Optimal m-learning engagement window (Sung et al., 2016)
Interaction Log Sampling	5	Seconds	Granular clickstream; minimal server overhead
Formative Assessments	16	Weekly quizzes	Continuous formative feedback (one per week)
Cognitive Skill Assessment Battery (CSAB) Item Count	50	Items	10 items × 5 cognitive dimensions
Score Scale (CSAB)	0–100	Marks	Normalised from a 2-point rubric per item
Reliability (Cronbach's α)	0.87	–	High internal consistency (acceptable ≥ 0.70)
Significance Level (α)	0.05	–	Conventional threshold for hypothesis testing
Effect Size Threshold (d)	≥ 0.5	–	Medium–large educational significance (Cohen, 1988)
Train/Test Split	80/20	%	Standard ML validation protocol
Cross-Validation Folds (k)	10	Folds	k-fold CV; balances the bias-variance trade-off
At-Risk Threshold	< 50	Engagement %	EDM literature benchmark (Arnold & Pistilli, 2012)
Engineered Features (ML)	28	Features	Clickstream + temporal + assessment + collaboration
LA Dashboard Update Freq.	Real-time	–	Server-side streaming via WebSocket API
Data Encryption Standard	AES-256	–	Compliance with institutional data protection policy

The sample size of N = 120 was calculated using a priori power analysis set at $\alpha = 0.05$, desired power $(1 - \beta) = 0.80$, and medium effect size $d = 0.50$ (a conservative estimate in line with previous m-learning meta-analytic standards). The minimum total sample required for the analysis was $n = 102$; the expected power of the provided sample $N = 120$ is around 0.87, which remained ahead of the standard threshold. For practical reasons, we chose a 5-second interaction log sampling rate capable of providing enough detail to meaningfully analyse the clickstream behaviour while ensuring processing on the server-side remained feasible in comparable LA deployments.

5.4 Instruments

CSAB. The main outcome measure was a 50-item CSAB, collected as pre- (week 0) and post-test measures (week 17, one week after the intervention had been completed). Through an empirical process guided by the principles outlined in Anderson and Krathwohl (2001), a total of 165 cognitive items were identified for the Computer Science Assessment Blueprint (CSAB). Items were based on the Collegiate Learning Assessment Plus (CLA+) instrument—a validated higher-order cognitive skills assessment widely administered for higher education quality measurement and supplemented with 18 domain-specific items that focused on cognitive operations relevant to data science, such as algorithm complexity evaluation, statistical output interpretation, and data quality estimation. Suitability of the adapted instrument was assessed by a panel of five subject-matter experts (three CSE faculty members and two cognitive assessment specialists) for content validity following a Content Validity Ratio method; all retained items reached CVR ≥ 0.60. Items were evenly distributed across five cognitive dimensions (10 items each): critical thinking, problem-solving, analytical reasoning, SRL strategies (assessed through scenario-based reflection items), and knowledge retention. Each item was scored according to a two-point rubric (0 = incorrect/absent; 1 = partially correct; 2 = fully correct and well-reasoned), resulting in dimension scores expressed on a normalised 0–100 scale. Cronbach's $\alpha = 0.87$ (acceptable internal consistency threshold: $\alpha \geq 0.70$) provides evidence for the internal consistency of the overall instrument, and test-retest reliability over a two-week interval in a pilot group ($n = 24$) was $r = 0.83$, indicating high temporal stability.

Multimodal data collection instruments. In addition to the CSAB, four supplementary data collection instruments were deployed. Weekly formative quizzes (10 items each, machine-graded, delivered via the mobile application) provided continuous performance monitoring data across all 16 intervention weeks. An SRL Strategies Survey—adapted from Pintrich et al.'s (1991) Motivated Strategies for Learning Questionnaire (MSLQ) and reduced to 12 items for mobile administration—was delivered in-application at weeks 4, 8, 12, and 16. Behavioural interaction logs were automatically generated by the mobile platform's event tracking system. A post-intervention Technology Acceptance Survey was administered at week 16 to measure perceived usefulness and ease of use of the mobile platform.

5.5 Data analysis procedures

Quantitative data analysis was conducted using Python 3.11 (scikit-learn 1.3, pandas 2.0, SciPy 1.11, and matplotlib 3.7) for machine learning analyses and SPSS Statistics 27.0 for inferential statistical tests. Pre-test and post-test score distributions were assessed for normality using the Shapiro–Wilk test; all distributions satisfied the normality assumption ($p > .05$), supporting the use of parametric test procedures. Homogeneity of variance across groups was verified using Levene's test prior to between-group comparisons. Research Question 1 (RQ1) was addressed through independent-samples t-tests comparing EG and CG post-test scores on each cognitive dimension and the composite score, with pre-test scores as covariates in sensitivity analyses. Research Question 2 (RQ2) was addressed through Cohen's d effect size computation, with interpretation guided by Cohen's (1988) benchmarks: $d = 0.20$ (small), $d = 0.50$ (medium), and $d = 0.80$ (large). Research Question 3 (RQ3) was addressed through the training and evaluation of seven machine learning classifiers using 10-fold stratified cross-validation, with model performance quantified through accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC–ROC). Feature importance was quantified using the Gini importance metric from the best-performing ensemble model.

5.6 Ethical considerations and research integrity

Institutional ethical clearance was obtained from the university's Research Ethics Committee prior to study commencement. All participants provided written informed consent specifying the voluntary nature of participation, the right to withdraw without academic penalty, and the data anonymisation and security protocols governing their personal data. Predictive modelling used anonymised assessment data, such that student identifiers were replaced with pseudonymous codes at the point of extraction from the platform database; access to these codes was restricted to the principal researcher in secure conditions. The study collected, stored, and analysed the data in accordance with India's Information Technology Act policy as well as our university's institutional data governance policy.

6 RESULTS

6.1 Pre-test equivalence verification

To ensure that the experimental and control groups were equivalent in terms of cognitive skill level before starting the intervention, independent-samples t-tests were performed on pre-test CSAB scores for the five cognitive dimensions. Table 2 shows the pre-test means and standard deviations of two groups. No statistically significant between-group differences were observed on any cognitive dimension (critical thinking: $t(118) = 0.35$, $p = .730$; problem-solving: $t(118) = 0.38$, $p = .703$; analytical reasoning: $t(118) = 0.28$, $p = .778$; self-regulated learning: $t(118) = 0.22$, $p = .825$; knowledge retention: $t(118) = 0.50$, $p = .620$; composite: $t(118) = 0.08$, $p = .935$). These results confirm that the EG and CG were cognitively comparable at baseline, consistent with attributing differences observed following treatment to the MLA framework intervention rather than pre-existing between-group variability.

6.2 Pre- to post-test cognitive skill development

Lastly, Table 2 provides descriptive statistics for the pre-test and post-test across all five cognitive dimensions as well as the composite score, in addition to independent-samples t-test results for between-group comparative analysis at the post-test. The experimental group showed significant and consistent improvements in all cognitive dimensions during the 16-week intervention period.

Table 2. Pre- and post-test cognitive skill scores: EG vs. CG (Mean ± SD, 0–100 Scale)

Cognitive Dimension	EG Pre	EG Post	CG Pre	CG Post	t-Value	p-Value
Critical Thinking	51.3 ± 6.2	74.8 ± 5.9	50.9 ± 6.4	61.2 ± 6.1	11.34	< .001
Problem Solving	49.6 ± 7.1	76.3 ± 6.4	50.1 ± 6.9	62.7 ± 6.8	12.47	< .001
Analytical Reasoning	52.1 ± 5.8	73.6 ± 5.7	51.8 ± 6.0	63.4 ± 5.9	10.82	< .001
Self-Regulated Learning	47.9 ± 7.4	71.2 ± 6.8	48.2 ± 7.2	59.3 ± 7.0	10.01	< .001
Knowledge Retention	50.4 ± 6.6	75.9 ± 6.1	49.8 ± 6.5	61.8 ± 6.3	12.09	< .001
Composite Score	**50.3 ± 6.6**	**74.4 ± 6.2**	**50.2 ± 6.6**	**61.7 ± 6.4**	**13.21**	**< .001**

Notes: EG = Experimental Group (n = 62); CG = CG (n = 58). All t-values reflect between-group post-test comparisons with pre-test scores as covariates. Degrees of freedom = 118. All p < .001 (two-tailed).

The EG's composite cognitive score increased from 50.3 ± 6.6 at pre-test to 74.4 ± 6.2 at post-test, representing a mean absolute gain of 24.1 points and a relative improvement of 47.9% over baseline. This gain substantially exceeds the CG's composite improvement from 50.2 ± 6.6 to 61.7 ± 6.4—a mean gain of 11.5 points (22.9% relative improvement). The between-group post-test difference of 12.7 points on the composite score was statistically significant ($t(118) = 13.21$, $p < 0.001$), directly and affirmatively answering RQ1. At the dimension level, the largest absolute gain in the EG was observed for problem solving (+26.7 points), followed by knowledge retention (+25.5), critical thinking (+23.5), SRL (+23.3), and analytical reasoning (+21.5). Corresponding CG gains ranged from +10.3 (critical thinking) to +12.6 (problem solving), confirming that the CG experienced modest learning gains attributable to standard instruction but failed to achieve the higher-order cognitive improvements characteristic of the MLA-treated group.

6.3 Feature importance analysis

Table 3 presents the Gini importance rankings for the ten most predictive features derived from the deployed XGBoost model, providing insight into the relative diagnostic informativeness of different learner data modalities and directly informing the operationalisation of early warning protocols.

Table 3. XGBoost feature importance rankings for at-risk prediction

Rank	Feature	Gini Importance	Interpretation
1	Assessment Trajectory Slope	0.187	The declining grade trend is the strongest risk signal
2	Weekly Login Frequency	0.154	Reduced logins precede disengagement
3	Time-on-Task per Session	0.139	Short sessions indicate superficial engagement
4	Module Completion Rate	0.118	Incomplete modules correlate with lower retention
5	Engagement Velocity (Week 4)	0.102	Early engagement drop is a critical risk predictor
6–28	Remaining Composite Features	0.300 (combined)	Forum participation, SRL survey, notification response

The most informative predictor, with a Gini importance of 0.187, was the slope of the assessment trajectory—essentially a Fibonacci-derived trend estimate—inferred from quiz scores over the previous four-week window (diagnostically dominant geometric aspects of longitudinal performance clearly surpassing ambient score points within cross-sectional snapshots). Second and third place were taken by weekly login frequency (0.154) and time-on-task per session (0.139), respectively, indicating that sustained behavioural engagement is a central risk signal during the early stages—a finding in line with the Signals system results as well as temporal engagement analysis. The relatively high ranking of the week-4 engagement velocity feature (0.102) supports theoretical framing around early intervention, showing that disengagement signals quantifiable as early as the fourth week in instruction are significantly predictive of end-of-semester at-risk status.

7 CONCLUSION

Finally, this study addresses a gap in the current literature on technology-enhanced learning by proposing and extensively evaluating an MLA framework based upon data science for cognitive skills development in undergraduate CSE education. In a 16-week quasi-experimental intervention of 120 undergraduate CSE students, the framework empirically showed statistically significant and educationally large advances in five targeted cognitive dimensions: (1) critical thinking, (2) problem solving, (3) analytical reasoning, (4) self-regulated learning, and (5) knowledge retention. Cohen's d effect sizes of 0.97 to 1.19 across these dimensions show that the MLA framework effects were not only statistically detectable but also educationally meaningful—improvements at a magnitude sufficient to materially change learners' readiness for data science-intensive professional positions. Using the framework, an XGBoost power predictive model generated 89.2% accuracy (AUC–ROC = 0.931) at identifying at-risk learners, enabling proactive, data-guided interventions which successfully recovered additionally flagged 72.7% of these learners above the at-risk threshold by mid-semester checkpoint measurement. Improving the Level Three Competence of the Try It Yourself Workshop: The Role of Experience; Kolb's Learning Style Theory: A Case Study on Learning from an Interactive Virtual Reality Application. Future work might overcome the limitations of this study via (a) multi-institution, non-overlapping cohort replication studies to establish external validity; (b) randomised controlled trial designs wherever institutional constraints allow them to enhance causal inference; (c) longitudinal follow-up assessments examining the salience of cognitive gains and their transfer into new data science task contexts; and/or qualitative investigations enriching our understanding of learners' subjective experience in respect to analytics-mediated metacognitive development that quantitative methods alone cannot cogently capture.

8 REFERENCES

[1] ABET, "Criteria for accrediting engineering programs, 2022–2023," Accreditation Board for Engineering and Technology, 2022. [Online]. Available: https://www.abet.org/accreditation/accreditation-criteria/

[2] L. W. Anderson and D. R. Krathwohl, Eds., *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Educational Objectives*. New York, NY, USA: Longman, 2001.

[3] K. E. Arnold and M. D. Pistilli, "Course signals at Purdue: Using learning analytics to increase student success," in *Proc. 2nd Int. Conf. Learning Analytics and Knowledge (LAK '12)*, 2012, pp. 267–270. https://doi.org/10.1145/2330601.2330666
[4] R. S. Baker and K. Yacef, "The state of educational data mining in 2009: A review and future visions," *J. Educational Data Mining*, vol. 1, no. 1, pp. 3–17, 2009. https://doi.org/10.5281/zenodo.3554657
[5] Y. Zhang, "Machine learning-based personalized learning path decision-making method on intelligent education platforms," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 16, pp. 68–82, 2024. https://doi.org/10.3991/ijim.v18i16.51009
[6] B. S. Bloom, Ed., *Taxonomy of Educational Objectives: Handbook I Cognitive Domain*. New York, NY, USA: McKay, 1956.
[7] S. Zemlyak, I. Nozdreva, and S. Sivakova, "Implementation of AI in smart logistics based on mobile technologies," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 17, pp. 88–100, 2024. https://doi.org/10.3991/ijim.v18i17.50735
[8] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794. https://doi.org/10.1145/2939672.2939785
[9] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum Associates, 1988.
[10] H. Crompton, "A historical overview of mobile learning: Toward learner-centered education," in *Handbook of Mobile Learning*, Z. L. Berge and L. Y. Muilenburg, Eds., New York, NY, USA: Routledge, 2013, pp. 3–14.
[11] H. Crompton and D. Burke, "The use of mobile learning in higher education: A systematic review," *Computers & Education*, vol. 123, pp. 53–64, 2018. https://doi.org/10.1016/j.compedu.2018.04.007
[12] M. Csikszentmihalyi, *Flow: The Psychology of Optimal Experience*. New York, NY, USA: Harper & Row, 1990.
[13] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989. https://doi.org/10.2307/249008
[14] B. Muruganantham, H. A. Karim, and S. B. Mansor, "Mobile health service adoption: Reducing the digital gap and age's moderating influence," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 17, pp. 139–153, 2024. https://doi.org/10.3991/ijim.v18i17.50741
[15] F. Faul *et al.*, "G power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences," *Behavior Research Methods*, vol. 39, no. 2, pp. 175–191, 2007. https://doi.org/10.3758/BF03193146
[16] L. Yang, "Quality optimizing teaching decisions in flipped classrooms through data-driven strategies," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 16, pp. 38–53, 2024. https://doi.org/10.3991/ijim.v18i16.51005

9 AUTHORS

Dr. S. Srividhya is currently working as an Assistant Professor in the Department of Data Science and Business Systems, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India. She obtained her Ph.D. in Computer Science and Engineering from SRM Institute of Science and Technology (SRMIST) in 2022 and her M.Tech from SASTRA University in 2014. Her research interests include data science, wireless sensor networks, intelligent systems, and interdisciplinary applications of artificial intelligence. She has published several research articles, book chapters, and conference papers in reputed journals and proceedings, with her work indexed in major databases such as Scopus and Google Scholar. With several years of academic experience, she is actively involved in teaching, student mentoring, and research in emerging areas of computing and data-driven technologies (E-mail: srividhs1@srmist.edu.in).

M. Ranjani was awarded the Doctor of Philosophy (Ph.D.) degree in Deep Learning from SRM Institute of Science & Technology, Department of Computing Technologies, Kattankulathur, India, in 2024. She is currently serving as an Assistant Professor in the Department of Computing Technologies, School of Computing, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur with over 10 years of teaching experience. Her research interests include Cryptography, Cloud Computing, Deep Learning, and Artificial Intlligence. She also serves as a reviewer for several international journals published by Elsevier and Springer (E-mail: ranjanim1@srmist.edu.in).

Dr. K. Rajesh Kumar is currently working in the MBA department, SRM Institute of Science & Technology, Tiruchirappalli. His expertise includes HR, Marketing, Supply Chain and Business Analytics. He has 3 ½ years of Industrial experience and 17 years of teaching experience. He has cleared SET and NET exams in management (E-mail: errajeshmba@gmail.com).

Dr. R. Praveenkumar presently serves as an Associate Professor in the Department of Electronics and Communication Engineering at Nandha Engineering College in Erode, Tamil Nadu. He earned his B.E. in ECE, followed by an M.E. in Communication Systems and a Ph.D. in Information and Communication Engineering, from Anna University Chennai, with an extensive 14 years of experience in Academic, Administration, Teaching, and Research, he is a highly accomplished professional in the field of Electronics and Communication Engineering, specializing in Mobile Networks. He has authored numerous articles published in various journals and actively supervises students undertaking their final-year projects at Anna University, Chennai. Additionally, he holds an active life membership in the Professional Society of ISTE, IAENG and NITTSD. His research interests encompass Networking, MANETs, Communication Networks, and various Technologies. He actively participates in college-wide activities and demonstrates strengths in maintaining a positive attitude, commitment, confidence, and effective teamwork (E-mail: rpraveenster@gmail.com).

P. Ramakrishnan is a distinguished academician and researcher in the field of Electronics and Communication Engineering, currently serving as Assistant Professor in the Department of ECE at M. Kumarasamy College of Engineering, Karur. He possesses over 14 years of teaching and academic experience, with substantial contributions to teaching excellence, research advancement, accreditation activities, and institutional development. His primary research interests encompass Wireless Communication, Cognitive Radio Networks, 5G Technologies, Machine Learning applications (E-mail: ramakrishnanp.ece@mkce.ac.in).