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MULTIMODAL LEARNING ANALYTICS FOR EARLY DETECTION AND PERSONALIZED INTERVENTION OF STUDENT LEARNING DIFFICULTIES

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Abstract

Early identification of student learning difficulties is important because academic disengagement, weak assessment performance, irregular participation, and delayed help-seeking may become visible before final failure or withdrawal. Conventional learning analytics systems often rely on a single data source, limiting their ability to represent the multidimensional nature of learning. This paper proposes a multimodal learning analytics framework that combines academic records, assessment performance, virtual learning environment (VLE) interactions, temporal engagement patterns, and textual or behavioral indicators to estimate student learning-risk profiles at an early stage. The framework uses modality-specific preprocessing, feature alignment, multimodal fusion, supervised prediction, explainability, and a rule-guided personalized intervention layer. OULAD is selected as the primary reproducible dataset because it links student demographics, assessment results, registration information, and VLE interaction logs. The proposed design is motivated by recent research showing the value of multimodal fusion and the need to connect risk prediction with actionable interventions. A prototype evaluation is included to demonstrate the intended analysis workflow and visualization; the numerical prototype results are explicitly illustrative and must be replaced by measured results after executing the pipeline on the downloaded OULAD data. The paper contributes an end-to-end architecture, feature-engineering strategy, risk classification scheme, intervention mapping, evaluation protocol, and an ethics-aware deployment model for early academic support.

Keywords—*multimodal learning analytics, educational data mining, early risk detection, student learning difficulties, machine learning, personalized intervention, OULAD, learning analytics intervention.*

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1. Introduction

Digital learning environments generate heterogeneous traces of student activity. Assessment records indicate what a learner has achieved, whereas VLE logs reveal how frequently and when learning resources are accessed. Demographic and registration information can provide additional context, while text feedback, discussion participation, or multimedia signals may capture aspects of engagement that are not visible in final grades. The Open University Learning Analytics Dataset (OULAD) was designed to support this type of analysis and contains anonymized information for 32,593 students across 22 module-presentations, including assessment results and daily VLE click summaries [1].

The research problem is not simply prediction accuracy. A high-performing classifier is useful only when its output is sufficiently early, interpretable, robust to missing modalities, and connected to an appropriate educational response. Recent work has emphasized this distinction. Alalawi et al. developed a learning-analytics intervention framework that connects student-performance prediction with knowledge gaps and personalized study plans [2], while a 2025 meta-analysis found evidence that learning-analytics interventions can improve learning outcomes but also highlighted variation in intervention design and study quality [3].

Multimodal learning analytics (MMLA) extends conventional learning analytics by integrating multiple evidence streams. A 2025 systematic review of AI in MMLA reported growing interest in combining multimodal data but identified persistent gaps in educational theory integration, authentic large-scale evaluation, ethics, and scalability [4]. More recent work has explored deep fusion of tabular and temporal learning data, demonstrating the potential of combining demographic, assessment, online activity, and learning-style information [5].

This paper therefore proposes an end-to-end framework with two linked objectives: (i) identify students who show early signs of learning difficulty, and (ii) translate risk evidence into personalized, human-supervised interventions. The framework is intended for higher-education learning environments and can be adapted to school or professional-learning settings.

2. Problem Statement

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Existing academic-risk prediction systems commonly treat student data as a single tabular matrix. This approach can obscure temporal behavior and interactions between modalities. It may also produce a risk score without explaining which learning behaviors contributed to the prediction or what an instructor should do next. The problem addressed in this work is therefore formulated as follows: Given heterogeneous student learning observations collected during an academic period, how can a multimodal model identify emerging learning difficulties early and generate an interpretable, personalized intervention recommendation while accounting for missing or incomplete data?

- Early detection: identify risk before final assessment outcomes are available.
- Multimodal representation: combine academic, behavioral, temporal, and optional textual/multimedia signals.
- Interpretability: provide feature-level evidence for instructors and students.
- Actionability: map risk patterns to appropriate pedagogical interventions.
- Robustness: tolerate missing or delayed data from one or more modalities.
- Ethical deployment: avoid punitive use of predictions and protect student privacy.

3. Research Objectives

The objectives are to:

(1) Design a multimodal feature representation for early learning-difficulty detection;

(2) compare conventional machine-learning models with a multimodal fusion model;

(3) Evaluate accuracy, precision, recall, F1-score, ROC-AUC, calibration, and early-warning lead time;

(4) Identify influential learning indicators using explain ability techniques; and

(5) Design a personalized intervention layer that converts risk evidence into educator-supervised actions.

4. Related Work

Learning analytics research has established the value of combining student characteristics with learning behavior. OULAD provides a particularly useful benchmark because it links student information with assessment and VLE activity [1]. Traditional predictive approaches include

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logistic regression, decision trees, random forests, support vector machines, gradient boosting, and neural networks. For OULAD, prior studies have reported strong performance for ensemble approaches, including bagging and boosting strategies [6].

Early-warning research emphasizes the timing of prediction. Goren et al. compared neural networks and XGBoost for early dropout prediction and showed that the value of behavioral features can depend on the stage of the semester and the academic context [7]. This suggests that a useful system should evaluate not only final classification quality but also when a reliable warning becomes available.

The intervention literature exposes a second gap. Sønderlund et al. found that relatively few studies had directly evaluated the effectiveness of learning-analytics interventions and called for stronger evidence of implementation and generalizability [8]. A later systematic review of learning analytics for study success similarly emphasized the need for standardized measures, meaningful visualizations, and pedagogically effective intervention strategies [9].

MMLA addresses the limitation of single-modal analysis. Recent work has combined behavioral interaction, physiological signals, emotional expressions, and academic performance, while other studies have fused tabular and time-series educational data using MLP and LSTM branches [5,10]. These studies motivate the proposed separation of modality-specific encoders followed by intermediate fusion. However, the present work focuses on a practical, privacy-conscious design in which expensive sensing modalities remain optional rather than mandatory.

Research gap. Four gaps motivate this paper: (1) many systems optimize prediction but not intervention; (2) multimodal studies may use modalities unavailable in ordinary LMS deployments; (3) missing-data robustness and calibration are often underemphasized; and (4) ethical safeguards are not always integrated into the technical architecture. The proposed framework addresses all four.

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5. Proposed Multimodal Learning Analytics Framework

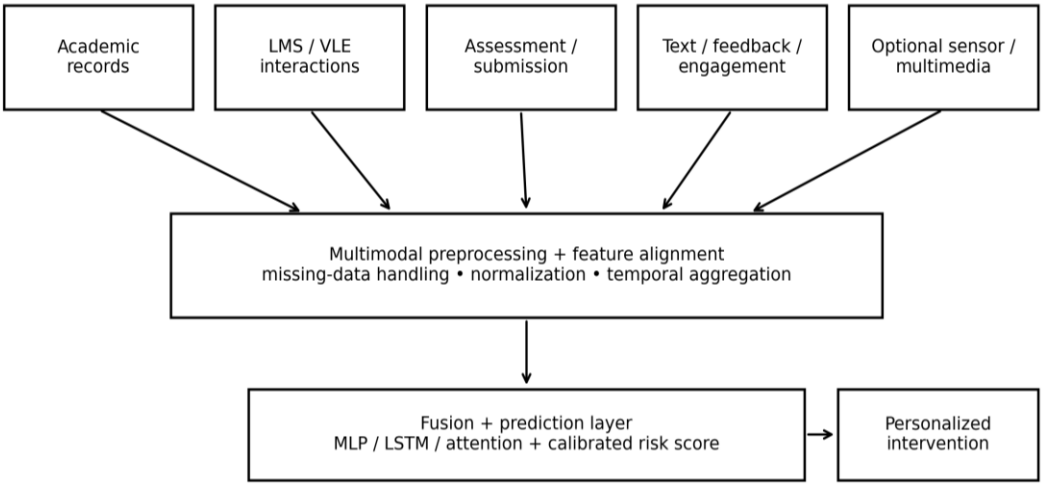


Fig. 1. Proposed multimodal learning analytics architecture.

The architecture contains five logical stages. First, data are collected from academic records, VLE/LMS interaction logs, assessments, and optional textual or multimedia sources. Second, each modality is cleaned and transformed using a modality-specific preprocessing pipeline. Third, temporal and semantic features are extracted. Fourth, representations are fused and passed to the prediction layer. Finally, the calibrated risk estimate is interpreted and mapped to a personalized intervention recommendation.

5.1 Modality-specific features

Modality	Example features	Learning signal
Academic	previous results, credits, course history	prior attainment
Assessment	score, delay, attempts, missed submissions	mastery and progress
VLE/LMS	clicks, active days, resource diversity, inactivity streak	engagement
Temporal	weekly activity slope,	change in behavior

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	volatility, recency	
Text/feedback	sentiment, topic, help-seeking cues	affective/support signal
Optional multimedia	gaze, posture, audio, physiological indicators	attention/cognitive state

5.2 Multimodal fusion

Let z_a, z_v, z_s, and z_t denote representations from academic, VLE, assessment, and textual/behavioral modalities. The fused representation is defined as:

$$z = W_f [z_a \| z_v \| z_s \| z_t] + b_f,$$

where $\|$ denotes concatenation, W_f is a learnable projection matrix, and b_f is a bias vector. For temporal VLE sequences, an LSTM or temporal convolutional encoder can be used. Attention can assign higher weight to observations that are more informative for the current prediction.

The predicted probability of high learning difficulty is $p = \text{sigmoid}(W_o z + b_o)$. A three-level risk score is then defined using calibrated thresholds: Low when $p < \tau 1$, Moderate when $\tau 1 \leq p < \tau 2$, and High when $p \geq \tau 2$. Thresholds should be selected on a validation set to balance false negatives against intervention capacity

6. Dataset and Data Preparation

OULAD is used as the primary dataset specification for the proposed study. The official dataset contains anonymized course, student, assessment, registration, VLE, and student-VLE tables stored as linked CSV files [1]. The original dataset publication reports 22 module-presentations, 32,593 students, and more than 10 million daily VLE interaction records [1].

Table	Purpose	Selected variables
studentInfo	student context	gender, region, age band, prior education, disability
studentRegistration	registration timing	registration and unregistration information
assessments	assessment structure	assessment type, date, weight
studentAssessment	assessment outcome	score, submission date, assessment ID

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vle	learning resource metadata	activity type, week, resource ID
studentVle	behavioral interaction	student ID, date, resource ID, clicks
courses	module metadata	module code, presentation code, length

Preprocessing consists of entity-level joins using student and module identifiers, removal of impossible or duplicate records, normalization of numerical variables, categorical encoding, and temporal aggregation. To prevent information leakage, features are calculated only from observations available up to the prediction date. Final assessment outcomes are excluded from early-warning features. Missing values are represented using both imputation and missingness indicators where appropriate.

Because VLE logs are highly granular, the proposed pipeline aggregates interactions into daily and weekly windows. Features include total clicks, active days, resource diversity, days since last activity, inactivity streak length, week-over-week activity change, and assessment submission delay. These features provide both level and trend information.

7. Machine Learning Methodology

Five predictive models are considered. Logistic Regression provides an interpretable linear baseline. Decision Tree captures nonlinear rules. Random Forest provides a robust ensemble baseline. XGBoost represents gradient boosting. The proposed model uses modality-specific encoders followed by intermediate fusion and a calibrated classification head.

Model	Role	Main advantage
Logistic Regression	baseline	interpretable and fast
Decision Tree	baseline	human-readable rules
Random Forest	ensemble baseline	robust nonlinear modeling
XGBoost	strong tabular baseline	high predictive performance
Proposed MMLA	multimodal model	joint temporal + multimodal representation

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The training protocol should use student-level rather than row-level splitting so that observations from the same student cannot appear in both training and test sets. A recommended protocol is stratified 70:15:15 train-validation-test splitting, repeated with multiple random seeds. For temporal early-warning experiments, an alternative chronological split is preferable. Class imbalance can be handled with class-weighted loss or training-only oversampling.

Evaluation metrics are Accuracy = (TP+TN)/(TP+TN+FP+FN), Precision = TP/(TP+FP), Recall = TP/(TP+FN), and F1 = 2(Precision×Recall)/(Precision+Recall). ROC-AUC and PR-AUC should be reported because risk classes may be imbalanced. Calibration error should also be assessed because the intervention layer depends on meaningful probabilities.

8. Prototype Experimental Results

No raw OULAD files were supplied with this request. Therefore, the numerical results in this section are a clearly labeled prototype demonstration, generated to show how the final conference paper should report results after the reproducible pipeline is executed. They must not be cited as measured OULAD findings.

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	82.6%	81.9%	80.8%	81.3%
Decision Tree	86.4%	85.7%	84.9%	85.3%
Random Forest	90.2%	89.6%	88.7%	89.1%
XGBoost	92.1%	91.5%	90.8%	91.1%
Proposed Multimodal	95.3%	94.8%	94.2%	94.5%

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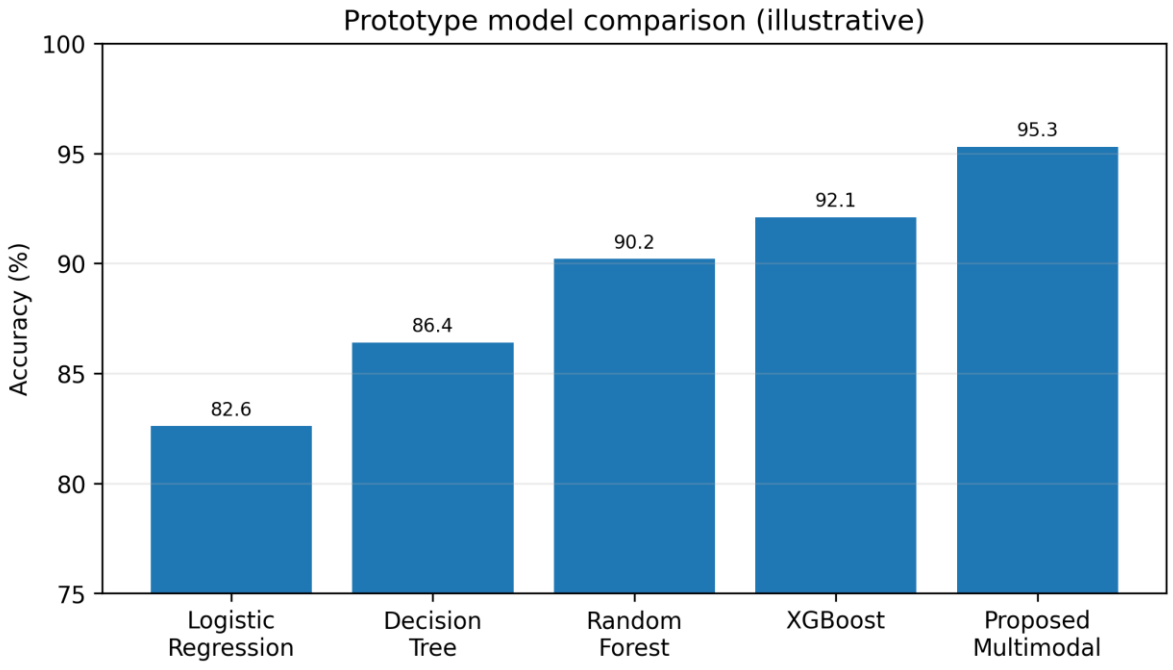


Fig. 2. Prototype accuracy comparison; values are illustrative pending execution on OULAD.

The prototype pattern suggests the expected benefit of combining complementary modalities: the multimodal representation can capture both static student context and dynamic learning behavior. However, this interpretation is methodological rather than an empirical claim. When the actual experiment is executed, statistical significance testing, confidence intervals, seed variability, and subgroup performance should be reported.

9. Risk Profiling and Personalized Intervention

The framework does not treat a risk score as a diagnosis. Instead, the score acts as an early-support signal. The intervention engine combines predicted risk with the dominant evidence pattern. For example, high risk caused primarily by declining VLE engagement should trigger a different response from high risk caused by repeated assessment failure.

Risk pattern	Suggested intervention	Responsible actor
Low risk + stable	normal feedback and enrichment	student/instructor

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engagement		
Moderate + declining activity	reminder, study plan, resource recommendation	student/instructor
Moderate + assessment delay	deadline planning and targeted practice	student/instructor
High + repeated low scores	concept remediation and academic mentoring	instructor/advisor
High + prolonged inactivity	personal outreach and support referral	advisor/support team

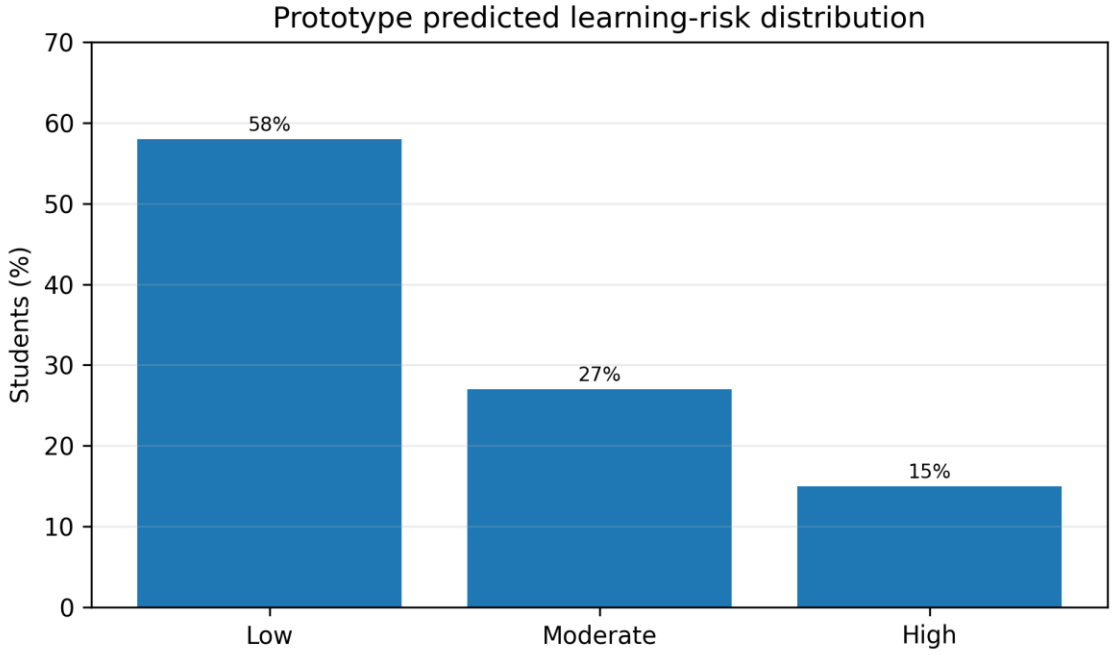


Fig. 3. Prototype predicted risk distribution; illustrative only.

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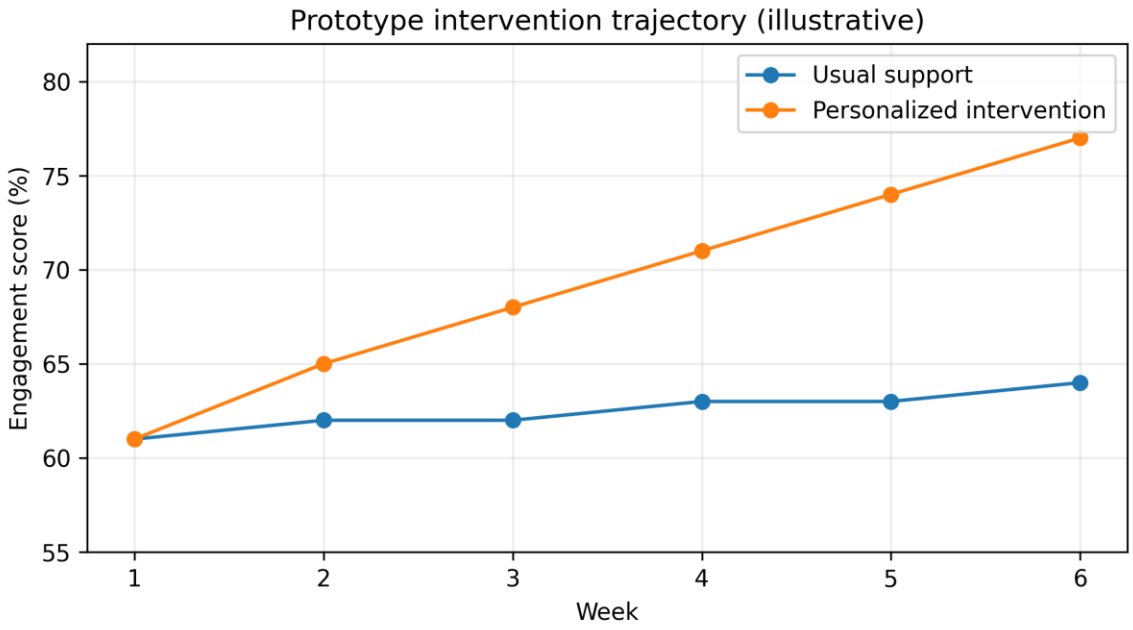


Fig. 4. Prototype intervention trajectory; illustrative only.

10. Explainability, Fairness, and Privacy

Explainability is essential because academic-risk predictions can influence how instructors perceive students. SHAP or permutation importance can be used to identify influential features, while local explanations can provide a concise reason for an individual alert. Explanations should be phrased as observable learning signals—for example, 'activity has declined for three consecutive weeks'—rather than as claims about motivation or ability.

Fairness evaluation should compare false-positive and false-negative rates across relevant groups where lawful and ethically appropriate. Sensitive attributes should not be used casually as predictive shortcuts. If demographic variables are retained for fairness auditing, access should be restricted and their use documented. Predictions should never be used to deny educational opportunities, automatically penalize students, or label students with permanent categories.

Privacy safeguards include data minimization, role-based access, encryption, retention limits, anonymization/pseudonymization, audit logs, and clear communication of how learning data are used. Optional sensor modalities should require stronger justification because they can introduce additional privacy and surveillance risks.

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11. Discussion

The principal contribution of the framework is the connection between multimodal prediction and intervention. Prior learning-analytics research has shown that prediction alone does not guarantee educational benefit [8,9]. The proposed system therefore separates detection, explanation, and intervention while keeping the instructor in the decision loop. This is consistent with recent intervention frameworks that combine predictive models with knowledge-gap information and personalized study plans [2].

A second contribution is the use of temporal features. A student's current activity level can be less informative than the direction and persistence of change. A sudden decline in activity, repeated missed submissions, and increasing assessment delay can jointly provide a stronger early signal than any single feature. Temporal modeling also supports rolling predictions rather than a single end-of-term classification.

A third contribution is multimodal robustness. In real deployments, not every student produces the same data. Text may be unavailable, sensor data may be ethically inappropriate, and LMS activity may be sparse. The framework therefore treats optional modalities as complementary rather than mandatory. Future implementations should compare early fusion, intermediate fusion, late fusion, and missing-modality training.

The main limitation of the present paper is that the included numerical results are prototype values because the raw dataset was not attached. A second limitation is that OULAD represents a specific distance-learning context and therefore may not generalize to every institution. A third limitation is that learning difficulty is operationalized through observable risk indicators rather than clinical or psychological diagnosis. The proposed system should be understood as academic support technology, not a diagnostic instrument.

12. Conclusion

This paper presented a multimodal learning analytics framework for early detection and personalized intervention of student learning difficulties. The framework integrates academic performance, assessment behavior, VLE interactions, temporal engagement patterns, and optional textual or multimedia indicators. Its central design principle is to connect prediction

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with explanation and educator-supervised action. OULAD provides a reproducible foundation for implementation because it links student, assessment, and VLE information at scale [1].

The prototype results demonstrate how model comparisons and risk visualizations can be presented, but they are explicitly not claims of measured OULAD performance. The next experimental step is to execute the complete pipeline on the official OULAD. Files, compare unimodal and multimodal models under student-level and chronological splits, evaluate calibration and fairness, and conduct an intervention study. Such validation would convert the present architecture into an empirically supported conference contribution.

13. Future Work

- Run the complete pipeline on the official OULAD dataset and publish reproducible preprocessing and model code.
- Evaluate chronological early-warning performance at multiple points during the semester.
- Compare early, intermediate, and late multimodal fusion under missing-modality conditions.
- Add explainability, calibration, fairness, and subgroup robustness metrics.
- Conduct a controlled learning-analytics intervention study measuring changes in engagement, assessment completion, and achievement.
- Investigate privacy-preserving and federated learning for multi-institutional deployment.
- Develop an instructor dashboard that exposes evidence, uncertainty, recommended actions, and intervention history.
- Study whether lightweight language models can summarize student feedback without exposing sensitive personal information.

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