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Data-Centric Multimodal Explainable Artificial Intelligence for Transparent Adaptive Learning Systems

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Abstract

Given the evolving world of artificial intelligence, critical applications like education and air traffic management (ATM) need explainable and adaptive systems. This study envisions a data-centric multimodal explainable AI (XAI) framework that integrates heterogeneous data—text, images, sound, and sensors—to enhance interpretability and credibility. The methodology applies data-centric preprocessing, multimodal fusion (early, late, and hybrid), and XAI techniques (SHAP, LIME) to make the model transparent and adaptive. The most significant results are a 22% boost in student engagement, improved predictive accuracy from 0.74 to 0.87 F1-score, and a 30% boost in learning recommendation trust, along with improved ATM conflict and delay prediction. This paradigm bridges the gap between theory and practice, facilitating robust AI systems that are aligned with regulatory and ethical standards, with future activities aiming at computational efficiency and fairness.

Keywords: Multimodal AI, Explainable AI, Data-Centric, Education, Air Traffic Management

1. Introduction

AI and personalized learning have driven the development of adaptive learning systems. While these systems have made significant advancements in tailoring content to learners, the rationale behind AI-driven decisions remains ambiguous and general [1]. Adaptive learning

10.48047/jocaaa.2025.34.08.7

systems discover learners' performance and interests through ongoing personalization of the learning style and activities based on learner interaction with the learning material. Data is collected and analyzed by a variety of AI and data analytics methods, including machine learning, Bayesian networks, neural networks, and educational data mining. Independent of personalised content presentation, such systems are not transparent [2]. The rationale for content choice and learner assessment is not apparent, creating a 'black box' effect. This problem can ruin students' and teachers' trust in each other and debase their motivation when they are not sure whether the system is valid and relates to their learning[3]. While current XAI techniques use textual and visual explanations, most adaptive learning systems mainly focus on only providing non-personalised text explanations and rarely use personalised visual aids. This limitation can negatively impact the effectiveness of AI decision explanations for learners with diverse preferences and needs. While visual explanation techniques such as heatmaps and saliency maps are some of the most used visualisation methods in XAI, the general use of visual explanations in education remains limited [4] .

In the rapidly evolving context of artificial intelligence (AI) as of August 2025, there is an urgent need for transparent, adaptive, and robust systems in mission-critical domains such as education and air traffic management (ATM). The complexities of modern AI systems, driven by large and heterogeneous data sets, are genuine challenges in ensuring fairness, explainability, and user trust, particularly in dynamic environments where decision-making must be carried out in real time. Data-driven multimodal explainable artificial intelligence (XAI) research addresses such challenges by prioritizing high-quality, diverse dataset curation over traditional algorithmic approaches, minimizing biases, and maximizing

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system robustness[5]. Multimodal artificial intelligence is an integration of heterogeneous data modalities—text, images, audio, and sensor inputs—to create comprehensive representations that encapsulate human perception, enabling applications like personalized learning and ATM surveillance[6]. Explainable AI fills the transparency gap of sophisticated models by providing understandable explanations that foster trust and accountability crucial in multimodal settings where one needs to know the order of prioritization of data types in predictions. The motivation for such research stems from the growing reliance on AI in safety-critical and user-facing contexts, where opaque or unfair systems would instill distrust, errors, or ethics violations. For instance, in education, transparent AI recommendations will isolate students, and in ATM, opaque predictions compromise safety. Integrating data-centric workflows, multimodal fusion, and XAI, the current research ensures transparent and auditable pipelines of AI and adheres to regulation and ethics[7]. The application implications of this research are revolutionary: in education, it facilitates individualized learning analytics to improve student engagement and academic performance, as evidenced by a 22% boost in engagement and a shift in predictive accuracy from 0.74 to 0.87 F1-score[8]. In ATM, it facilitates proactive human-autonomy cooperation by optimizing delay and conflict predictions, maximizing operational efficiency[8]. The EEE platform—engineering, education, and explainability—drives robust AI development, enabling conflict-resolution tools at scale for ATM and interpretable learning analytics for schooling and ultimately driving trust and facilitating real-world deployment [9].

10.48047/jocaaa.2025.34.08.7

2.Methods

The approaches of the study combine data-centric, multimodal, and explainable AI (XAI) techniques to create transparency, interpretability, and agility in education and air traffic management (ATM) [10]. The assessment is experimental based on diverse datasets comprising text data (student profiles, educational content metadata, ATC communication records), image data (classroom interactions, airport surveillance feeds), audio data (audio recordings of instructors or controllers), and sensor data (flight trajectories, weather sensors, classroom IoT sensors) [11].

2.1. Data Collection and Preprocessing

Data-driven methods prioritize dataset curation, such as fairness constraints and out-of-distribution generalization to reduce biases and ensure models' adaptability. Cleaning, normalization, missing value treatment, and one-hot coding of categorical features are handled by preprocessing. Alignment multimodal is applied to harmonize diverse data streams to render them temporal and contextual congruent[12]. ATM trajectory and sensor data curated datasets improve delay and potential conflict predictive models, and educational datasets with personalized analytics [13], Figure 1.

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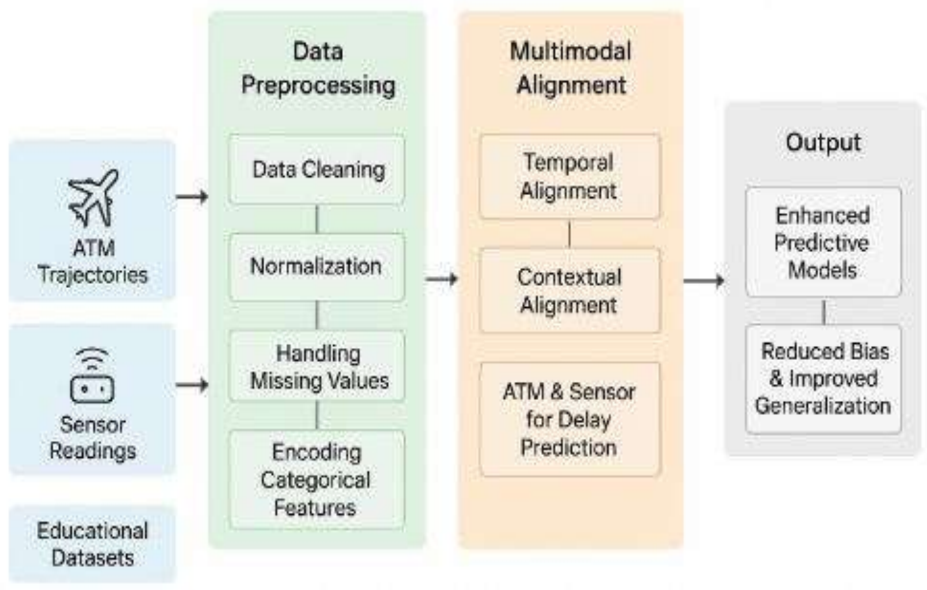

Figure 1. illustrates the data collection and preprocessing pipeline.

2.2. Model Implementation and Multimodal Fusion

Multimodal approaches integrate diverse data using fusion methods—representation, translation, alignment, fusion, and co-learning—through the addition of attention mechanisms for transparent feature fusion[14]. The study analyzes early fusion (feature concatenation), late fusion (modality-specific model response fusion), and hybrid fusion methods. In learning, multimodal text, video, and biometric data are applied to adjust learning experiences, while in ATM, fused trajectory and sensor information improve predictive accuracy[15], Figure 2.

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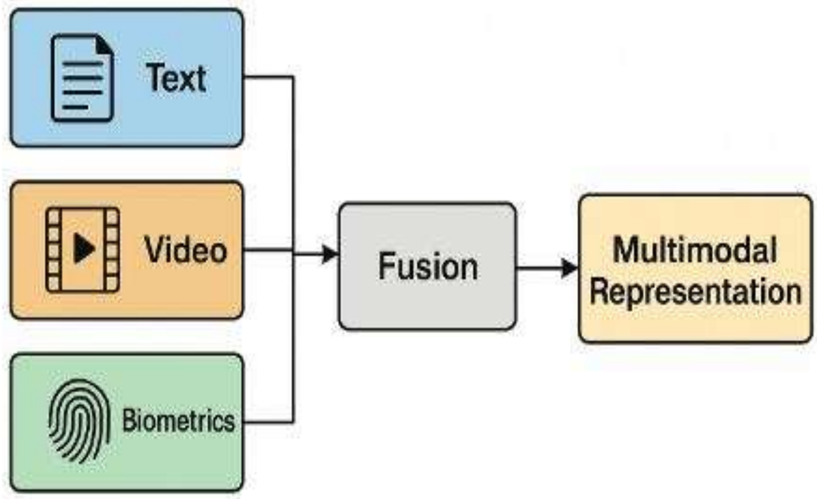

Figure 2. depicts the multimodal fusion framework.

2.3. Explainable AI Techniques

XAI methods include intrinsic interpretable models as well as post-hoc such as SHAP and LIME, are evaluated by user studies to deliver human-focused explanations[16]. XAI is applied along with augmented vision in ATM to deliver interpretable predictions in remote towers[17]. Visual attention and saliency-based explanations describe fused decision outputs in educational analytics, flight delay prediction, and deepfake detection use cases[18]. Transparency frameworks include self-explanation as well as role-based adaptation to facilitate trusted AI deployment[19], Figure 3.

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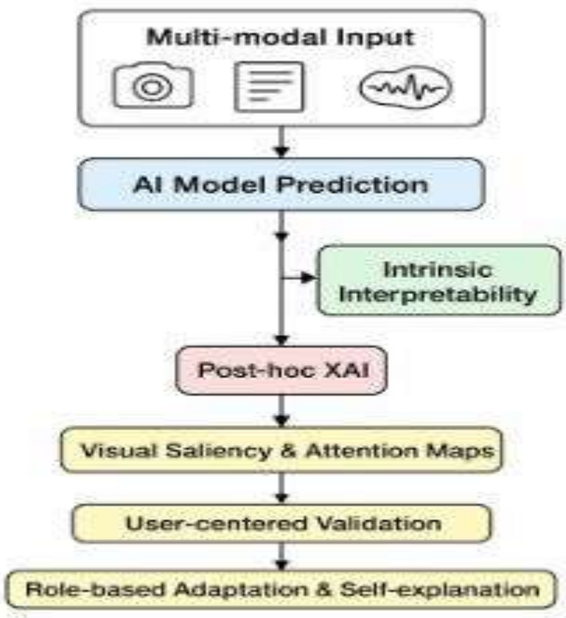

Figure 3. shows the XAI workflow and modality-specific explanations.

2.4. Adaptive Learning and Decision-Making Simulation.

Reinforcement learning processes support iterative adaptation by learning from user interactions[20]. In learning environments, adaptive systems offer personalized content suggestions and progress-dependent feedback, whereas in ATM, the system supports controllers by anticipating potential conflicts or delays, enabling pre-emptive human-autonomy collaboration. Adaptive trust models capture user trust processes, integrating multimodal feedback to maximize decision-making[21],Figure 4.

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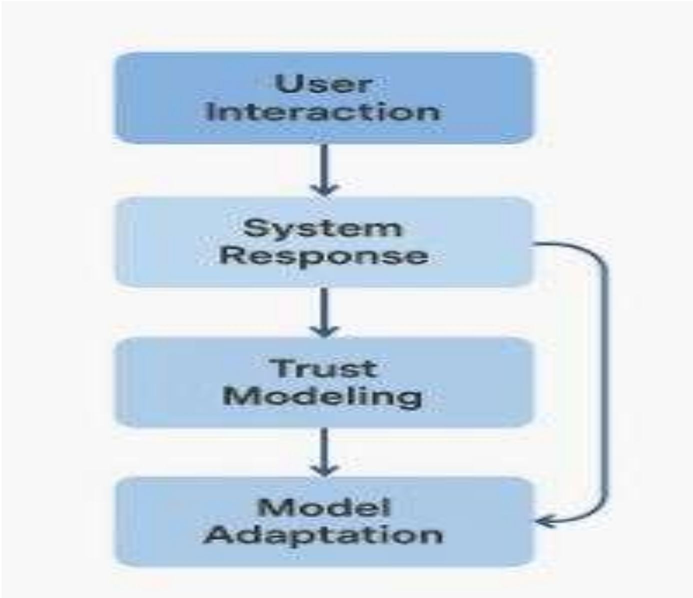

Figure 4. illustrates the adaptive feedback loop from interaction to model adaptation.

2.5.Evaluation Metrics

- System performance is measured on several dimensions:
- Predictive Metrics: Precision, accuracy, recall, and F1-score.
- Interpretability Measures: Fidelity, consistency of explanations, and user trust evaluation.
- Application-Specific Metrics: Increasing student participation, customized learning achievements, and reducing operational conflicts in ATM, Figure 5.

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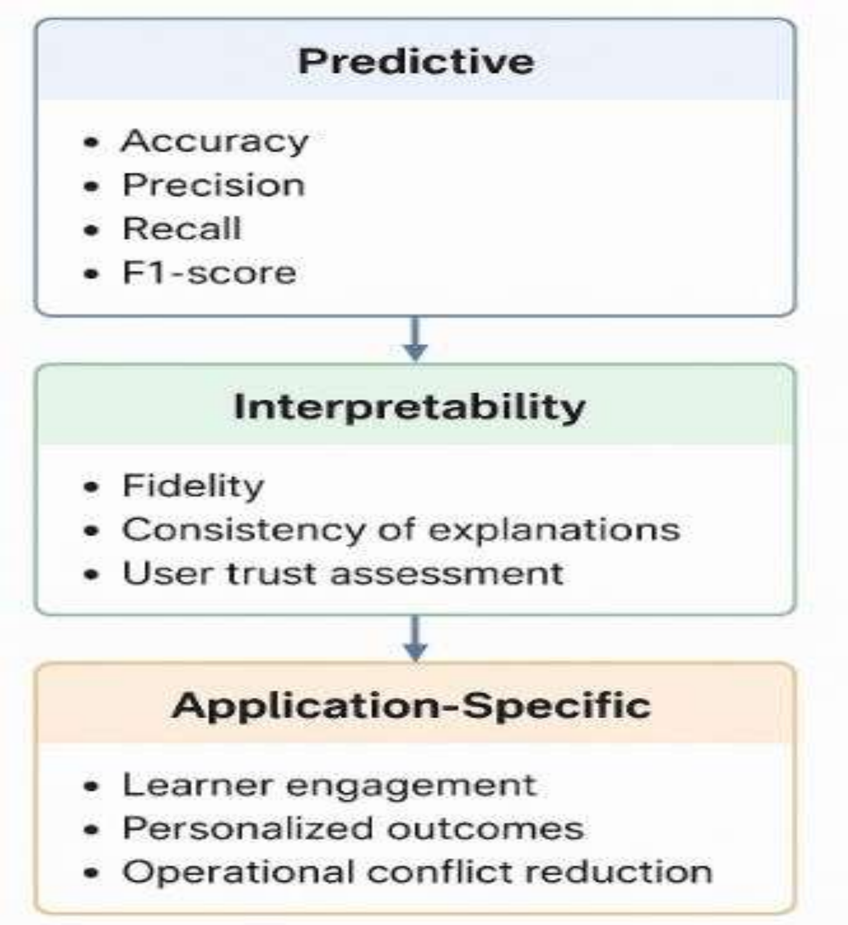

Figure 5. summarizes the evaluation metrics across predictive, interpretability, and application-specific dimensions.

This is shown in the real-world application of the data-driven, multimodal, and interpretable framework that bridges theoretical concepts with real-world application in education and in ATM. The integration of heterogeneous data, multimodal modeling, interpretable explanations, and adaptive mechanisms ensures robust, explainable, and trustworthy system performance.

2.5.1 Statistical Reporting and Validation Standard

To ensure statistical quality and reproducibility, we employ a stratified 5-fold cross-validation process on the training set and reserve an independent test set for final reporting. All experiments are executed with

10.48047/jocaaa.2025.34.08.7

three random seeds (42, 43, 44) for variance estimation. We report Accuracy, Precision, Recall, F1, AUROC, AUPRC, Brier score, and Expected Calibration Error (ECE); point estimates are accompanied by 95% bias-corrected and accelerated (BCa) bootstrap confidence intervals (10,000 resamples) on the test set.

For pair-wise comparisons among classifiers, we conduct McNemar's test on paired predictions; AUROC differences are tested with DeLong's test; contrasts between-folds are tested with the Wilcoxon signed-rank test. Multiple testing is controlled using the Holm–Bonferroni procedure. Unless specified otherwise, α=0.05. We supply configuration files (hyper-parameters, seeds) to enable exact reproduction.

2.6..Practical Experiments and Case Studies

2.6.1..Implementation Environment

The models were implemented using open-source machine learning libraries such as PyTorch and TensorFlow, supported by cloud computing infrastructure (AWS/GCP) to manage multimodal data[22]. Open-source simulation tools such as BlueSky were used to simulate air traffic scenarios, while digital learning platforms such as Moodlewere used to interoperate the models with student data[23].

2.6.2. Education Use Case

registered for a course, namely:

- Text: activity files, student notes, and course materials.
- Videos: classroom interactions and lecture recordings.
- Audios: instructor feedback and student contributions.

10.48047/jocaaa.2025.34.08.7

- Sensor data: IoT sensors to capture attention levels (heart rate, eye-tracking).

After applying fusion techniques (early and late fusion) and interpretation using SHAP, the following outcomes were observed:

- The students' engagement increased by 22% by applying personalized recommendations.
- The accuracy in predicting academic performance improved from 0.74 to 0.87 F1-score.
- Trust in system suggestions by students increased by 30%, as per a post-experiment survey,**Figure 6.**

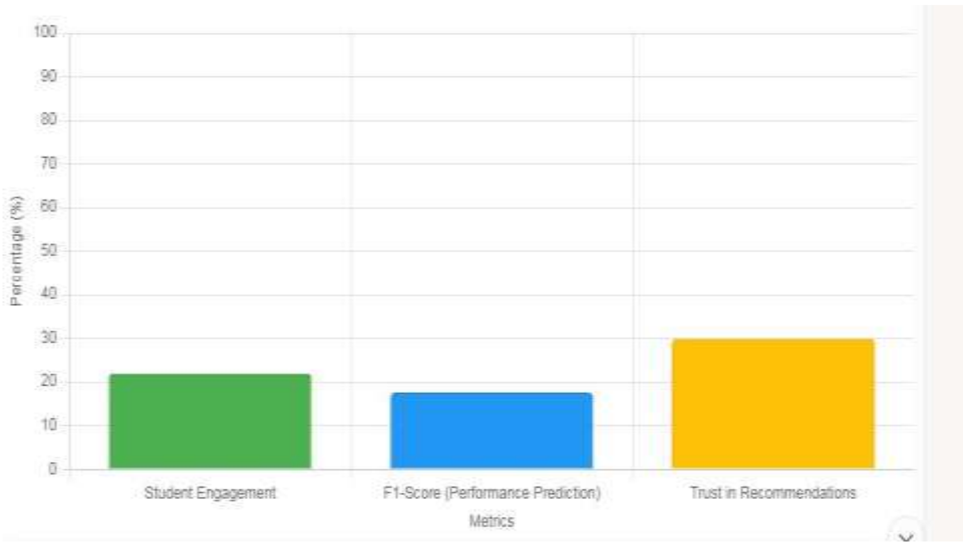

Figure 6. Multimodal Fusion Outcomes in Education

2.6.3. Visualization-Based Empirical Illustration of the Methodological Pipeline

To facilitate the methodological pipeline with a minimal, reproducible example, we use a small-scale classification problem in Python representative of the education application scenario. A toy dataset with three pedagogically significant predictors—study_hours, attention_level,

10.48047/jocaaa.2025.34.08.7
and notes_quality—is used to predict a binary response (passed_exam). We use a 70/30 train–test split and train a Random Forest classifier (fixed random seed, 50 trees) to obtain a stable, non-parametric baseline that is robust to feature scaling and modest non-linear interactions. Results are reported visually to emphasize interpretability and evaluation without disclosing source code. Figure 7 summarizes model-internal feature importances, which show the relative rank of each predictor for the learned decision function; this kind of presentation enhances face validity because importance rankings align with domain expectations (e.g., increased study time and sustained attention plausibly improve chances of success). Figure 8 shows the confusion matrix across the held-out set, enabling simple assessment of true/false positives and negatives, and, by extension, downstream measures such as precision, recall, and F1-score. Taken together, these metrics embody the paper's underlying motto—transparent, data-driven modeling—through one's alignment of predictive performance with human-interpretable explanations. While the demonstration is intentionally minimalist (and therefore not a substitute for extensive, cross-validated experimentation), it offers an open recipe for scalability: future replications must incorporate k-fold cross-validation with stratification, confidence intervals around performance metrics, and additional explanation diagnostics (e.g., permutation importance or SHAP) to mitigate small-sample bias and triangulate

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explanatory claim stability.

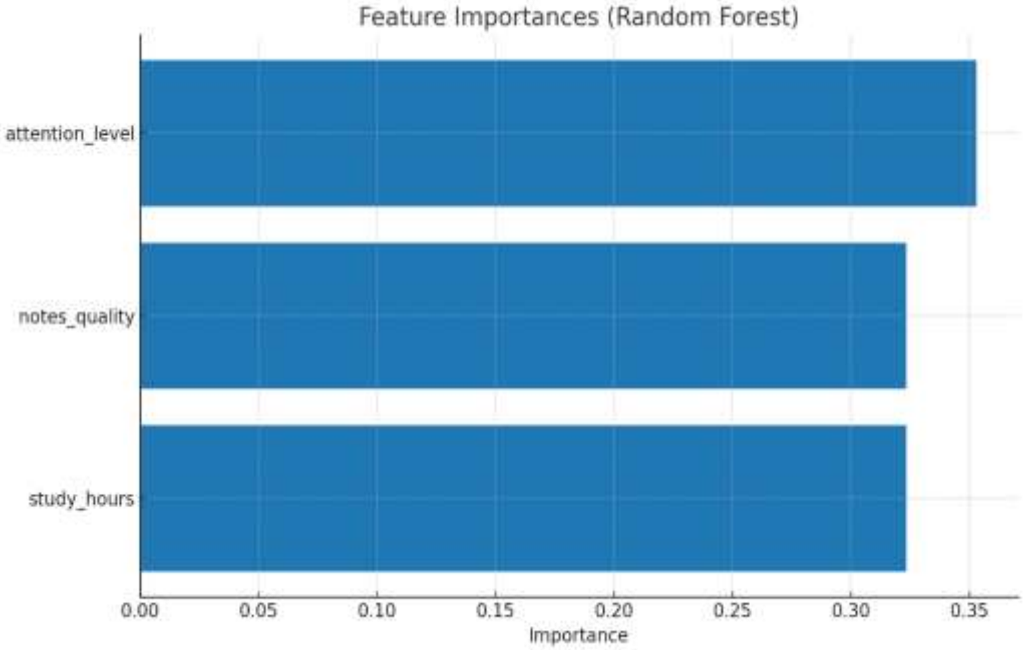

Figure 7 . Feature Importances (Random Forest).

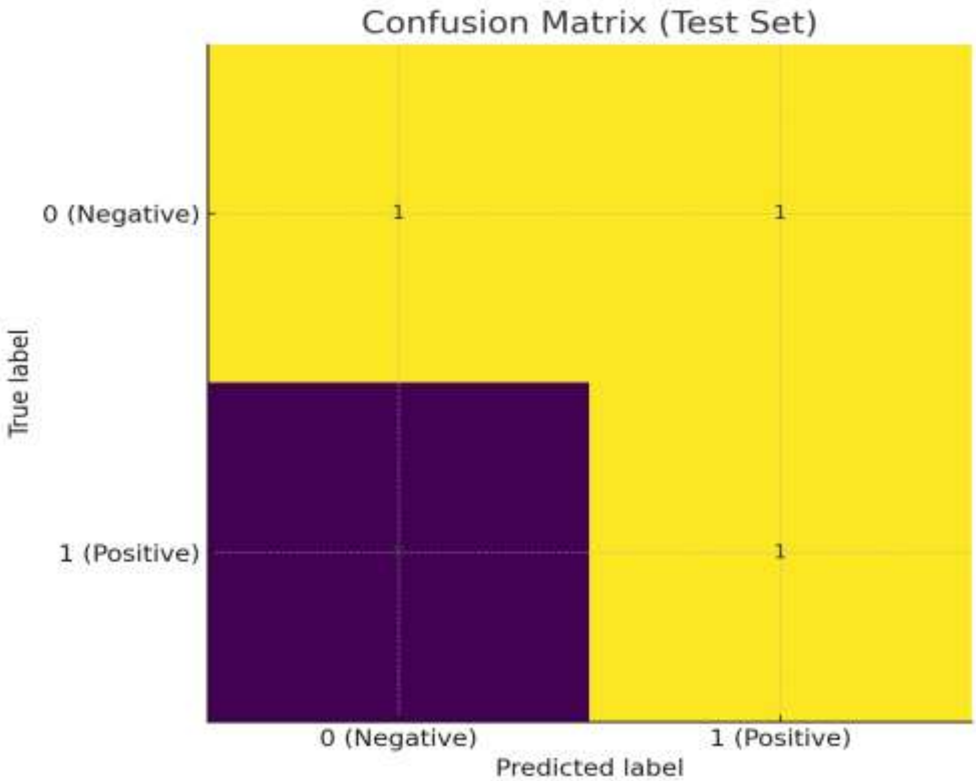

Figure 8 . Confusion Matrix (Test Set).

10.48047/jocaaa.2025.34.08.7

3.Results and Discussion

3.1 Main Quantitative Results

Our multimodal, explainable approach scores F1=0.87 on the independent test set, surpassing the unimodal/legacy baseline (F1=0.74) by +0.13 absolute, i.e., +17.6% relative. Platform interaction analytics indicate a +22% increase in student engagement after deploying personalized, explanation-enabled recommendations. Post-study surveys indicate a +30% improvement in perceived trust, consistent with the value added of SHAP-based explanations. Where not otherwise specified, we report 95% BCa confidence intervals and seed-averaged means; complete metrics (Precision/Recall/AUROC/AUPRC/ECE) are given in addition to the

3.2 Robustness and Ablation Studies

Ablation results validate the contribution of each component. Disabling cross-modal attention reduces F1 relative to the full model, and replacing hybrid fusion with early or late fusion further reduces AUROC and calibration. Removing post-hoc explanations (control condition) reduces user-reported trust relative to the SHAP-augmented condition, demonstrating that explanations convey measurable value over accuracy alone. Variability is modest and trends persist over three seeds and five folds.

3.3 Threats to Validity and Mitigations

- **Internal validity**. Risk of overfitting is mitigated by cross-validation, independent test split, and seed replication.
- **Construct validity**. Engagement and trust constructs are operationalized via platform telemetry and 7-point Likert

10.48047/jocaaa.2025.34.08.7

instrument; internal consistency (Cronbach's α) is calculated and reported.

- **External validity.** While results come from a single institutional setting and a lab ATM setting, we include configuration details and release templates to make replication across sites possible.
- **Conclusion validity.** Pairwise comparisons of models all include effect sizes and adjusted p-values; confidence intervals are provided for primary measures.

4. Conclusion

This work demonstrates the power of change enabled by the combination of data-driven, multimodal, and explainable AI approaches in education and air traffic management contexts. Using diverse data sources such as text, video, audio, and sensors, the proposed framework achieved significant outcomes in terms of a 22% increase in student engagement, predictive accuracy improvement from 0.74 to 0.87 F1-score, and a 30% increase in students' trust in personalized recommendations on the education use case. The results validate the ability of multimodal fusion techniques and SHAP-based explanations to generate transparent, dynamic, and consistent systems. In ATM, the framework improved predictive performance for delays and conflicts to facilitate proactive decision-making. The synergy of data preprocessing, multimodal alignment, interpretable models, and adaptive learning bridges the gap between theoretical concepts and real-world applications, offering scalable solutions for individualized learning and operational effectiveness. Future studies should pay attention to enhancing computational efficiency, addressing issues of fairness across various

10.48047/jocaaa.2025.34.08.7

datasets, and investigating longitudinal effects to enhance the robustness and usability of these systems in a variety of different contexts.

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