Accurate Matching And Recommendation For University Innovation Projects: A Multimodal Mobile Learning Approach

Xiangge Liu, Bingquan Yin , Yali Hou, Benzhuo Fu, Qi Chen, and Haijuan Zhou*

Qinhuangdao Vocational and Technical College, Qinhuangdao 066000, China

Corresponding author. E-mail: haijuan_zhou95@outlook.com

Received: Mar. 01, 2026; Accepted: Apr. 06, 2026

University innovation projects are increasingly complex and require personalized recommendation systems that align students' academic strengths with appropriate project opportunities. Existing recommendation methods typically rely on limited academic criteria, which fail to capture the full diversity of student learning characteristics, resulting in suboptimal matching. To address this, the research proposes an integrated mobile learning-based system that utilizes structured academic data from students' marksheets. The framework distinguishes multiple modalities, including overall academic performance (GPA, weighted GPA), subject-domain proficiency (subject-wise scores), and temporal learning trends (semester-wise performance variations). Although these features originate from a single dataset, they represent distinct perspectives on student learning. Each modality is transformed into a feature representation, and these heterogeneous representations are combined into a unified multimodal student profile through vector-level fusion. A collaborative filtering-based recommendation engine, powered by cosine similarity, then generates personalized project suggestions. The system's effectiveness is evaluated using standard recommender metrics such as Precision@5, Recall@5, F1@5, NDCG@5, MAP@5, hit rate, and coverage. Experimental results demonstrate the proposed method outperforms baseline approaches, achieving improvements of 12.6% in Precision@5 and 9.8% in NDCG@5, indicating enhanced ranking accuracy and recommendation relevance. Overall, the findings confirm that multimodal academic representations significantly improve personalized and large-scale innovation project recommendations in higher education.

Keywords: Multimodal Recommendation, Mobile Learning, Collaborative Filtering, Innovation Project Matching, Educational Data Mining

http://dx.doi.org/10.6180/jase.202609_32.063

1. Introduction

1.1. Background and Motivation

The rapid growth of technology has led to innovative educational systems [1], with universities using mobile learning platforms to provide personalized recommendations [2]. These platforms support students' imagination and practical skill development through innovation projects [3][4], yet implementing effective multimodal recommendation systems remains challenging [5].

In university project allocation, challenges may include insufficient project slots, mismatch of student skills, and uneven distribution of projects. Many students receive mismatched or unallocated projects, needing personalized recommendations.

1.2. Key Factors Influencing Personalized Recommendations

Educational recommendations rely on multimodal data [6], supported by studies advocating multi-source approaches

[7]. Text-only systems miss aspects like creativity or emotional engagement [8]. Student preferences and engagement are crucial [9], and integrating multimodal data enables diverse, personalized recommendations meeting varied learning needs [10].

Existing educational recommendation systems are mostly based on simple academic criteria, such as GPA and student profiles. Proposed research uses multimodal features.

1.3. Challenges and Limitations in Multimodal Systems

Multimodal recommendation systems face challenges [11], including complex text, audio, video integration [12], data privacy and bias [13], and limited real-time updates [14][15].

1.4. Proposed Solutions

Technique uses ML and multimodal data for accurate, scalable personalized recommendations.

1.5. Objective

- Build personalized university project recommendation using multimodal student data.
- Use marksheets: GPA, scores, performance trends.
- Fuse features into multimodal academic representations.
- Apply collaborative filtering with cosine similarity via mobile platform.

2. Literature review

Research highlights the need for standardized multimodal recommendation frameworks [16], personalized learning [17][18], and evolving multimodal fusion algorithms with benefits and limitations [19].

Methods like MMAM [20] and GEMRec [21] handle missing multimodal data using adversarial learning and graph features. Neural networks [22] enhance personalization, with positive acceptance [23], adaptive education [24], and improved accuracy via METRIC [25].

As artificial intelligence and intelligent sensor technologies have advanced, the traditional legal English teaching methods have faced challenges in dealing with multimodal information and complex reasoning. [26]. Deep learning (DL) transformed medical image analysis by allowing for timely anomaly detection, accurate lesion segmentation, and disease classification [27].

Lack of data caused advising issues; unified pipeline predicts dropout, recommends programs. [28]. A management system for college students' innovation and entrepreneurship education using a B/S architecture. The study focuses on improving the efficiency of managing educational activities and student projects through a web-based system. [29]. A hybrid deep learning model that integrates CNNs for feature representation and GANs for generating synthetic data in detecting UI defects with high accuracy while overcoming issues of less labeled data and inefficient manual testing.

Relationships are modeled in graph models, robustness is added in adversarial models, and multiple data types are combined in multimodal models, which are the most suitable for student-project recommendations.

2.1. Problem Statement

The complexity of university innovation projects necessitates accurate, flexible recommendation systems linking students to suitable projects based on profiles, interests, and skills. Traditional methods using limited data and lacking multimodal integration of text, audio, video, and interaction logs often fail to capture project suitability effectively.

3. Proposed model

The cosine similarity is calculated between the feature vector of students (GPA, subject scores, and performance trends), and the projects associated with the neighbors are recommended for the purpose of personalized suggestions.

Framework uses preprocessed student marksheets to guide innovation initiatives Fig. 1.

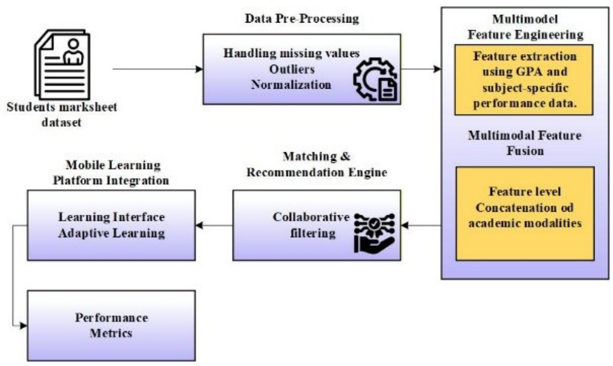

Fig. 1. System Architecture for Collaborative Filtering-Based Project Recommendation

Multimodal feature engineering creates student embeddings driving collaborative filtering recommendations, delivered via mobile learning, evaluated with precision, recall, F1-score, NDCG, MAP, and coverage.

3.1. Data Collection

The first step collects subject marks and student profiles, providing a complete view of academic history, behavior, and preferences for tailored projects.

Dataset link:

https://www.kaggle.com/datasets/rohithmahadevan/students-marksheet-dataset

3.2. Data Pre-Processing

Data preprocessing is needed on the raw data, so that any missing values and outliers are handled, and the data are modelled and normalised for analysis.

The student marksheet dataset was divided in the ratio of 80 : 20 to form the training set and test set, where the training set was used to train the model, and the test set was used to evaluate the metrics like Precision, Recall, and NDCG in a transparent manner.

3.2.1. Handling Missing Values

It is common for large datasets to have missing values. Such cases can be handled either by imputation or deletion. One of the most commonly used methods of imputation is the mean, which replaces the missing values with the mean of the respective column. Mean imputation was adopted for missing data imputation because it is simple and efficient in maintaining data distribution. Other methods like median, mode, and prediction imputation were also considered but not implemented based on data properties and computation efficiency.

$$x_{\text{new}} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

Where:

x_{new} represents the imputed value. x_i represents individual data points in the dataset. The total number of data points is denoted by n.

3.2.2. Outliers

Outliers are detected and treated by deletion or statistical methods like Z-score to ensure accuracy.

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

Given:

Data point is x, The data mean is denoted by μ, The standard deviation is represented by σ, Outliers are generally defined as data points in the $z > 3$ zone. The Z-score threshold of 3 was used to detect outliers, validated against known abnormal cases for accuracy.

3.2.3. Normalization

Normalization scales features uniformly, often using Min-Max to range 0-1.

Where:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

x_{norm} represents a normalized value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the feature. Mean imputation is used to fill in the missing values, the Z-score is used to identify the outliers, and the min-max normalization is used to normalize the features to a certain scale, thereby ensuring the accuracy of the student similarity calculation in the collaborative filtering process.

Feature normalization equally scales GPA, scores in different subjects, and performance trends, thereby preventing dominance in the features and improving the accuracy of the cosine similarity in collaborative filtering.

3.3. Multimodal Feature Engineering

Feature engineering creates or modifies features; extraction selects features efficiently.

Engineered features such as GPA, subject-wise averages, and semester-wise trends in student performance are used to generate student feature vectors.

GPA, subject scores, and semester-wise trend represent different aspects of student information. Features from one database fuse, enhancing student representation for recommendations.

Student embeddings are formed based on the combination of GPA, subject-based scores, and performance trends. Each of these features is represented numerically, and they are concatenated to form a unified representation. For example, the combination of 1 value for GPA, 5 values for subject scores, and 1 value for the trend will create a student embedding with 7 dimensions. Subject domain proficiency is derived from weighted subject scores, which represent student strengths and inform recommendations for the project accordingly.

Multimodal academic measures such as GPA, scores in different subjects, and trends in semester-wise academic performance are combined using a technique called feature-level fusion to create a unified representation of the students in the form of embeddings, which take into account the different learning abilities of the students.

Multimodality in EDM involves the combination of GPA, scores in different subjects, and semester trends in a student's records to form a numerical embedding that reflects different learning characteristics.

3.3.1. GPA Calculation

GPA can be considered as one of the main signs for predicting a student's academic success in general. It is calculated as an average of grades obtained in various subjects.

$$\text{GPA} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

Where:
x_i is the mark achieved in the i subject. w_i is the weight given to the i subject (according to its significance or credit hours). n is the overall number of subjects.

3.3.2. Subject-Specific Features

Traits indicate student performance, assessing skills for project-related subjects.

$$\text{Subject Average } = \frac{\sum_{i=1}^{n} x_i}{n} \tag{5}$$

Where:
x_i is the mark in the subject that the student has obtained. Let the number of subjects considered for one student for their marks be n.

3.3.3. Performance Trends

During this phase, the performance of the student over time is traced to investigate improvement (or lack of it) in the student's academic ventures.

$$\text{Performance Trend} = \frac{\text{Current GPA} - \text{Previous GPA}}{\text{Previous GPA}} \times 100 \tag{6}$$

Therefore:

Current GPA is the GPA achieved in the latest semester. The GPA for the past semester, on the other hand, is the previous GPA.

3.4. Multimodal feature fusion

Feature extraction selects subject scores, GPA, and performance trends, creating a multimodal representation fused for collaborative filtering-based personalized project recommendations.

The temporal academic pattern also influences the recommendation process, where improving students are assigned more advanced projects, while declining students are guided toward basic projects, thereby affecting the final recommendation scores.

Semester-wise performance trends are also taken into account while making recommendations. This helps in guiding the students towards advanced or foundational projects. This information is incorporated in the feature vectors for similarity scoring.

The student representations are updated based on the availability of the performance data for the new semester. New feature vectors are computed using the updated information in the student's GPA, subject grades, and trends, as well as the similarity scores.

3.4.1. Matching & Recommendation Engine

Collaborative Filtering analyzes student interactions, using Pearson Correlation and Cosine Similarity to recommend projects based on student interests and similarities.

The student-project interaction matrix was constructed using academic attributes such as weighted GPA and domainspecific scores. Attributes converted to vectors, computing similarity.

Cosine similarity is used because of its efficiency in dealing with high-dimensional feature vectors and its ability to identify similarity in student profiles. Among Pearson correlation and adjusted cosine similarity, this method is simpler and better for feature-based academic data.

Data sparsity might decrease accuracy in measuring similarity and influencing recommendations. Nevertheless, utilizing structured features such as GPA, scores, and trends is helpful in creating dense data and improving performance.

Cosine similarity was chosen due to its efficiency in handling high-dimensional student features and its applicability in feature-based academic data, unlike the Pearson or adjusted cosine measures.

The outputs of the recommendation engine are integrated into the mobile platform, and the interface allows the students to explore the projects that match their academic profile.

The distribution chart for the project recommendations demonstrates the number of recommendations made for each project. Projects with high popularity are recommended multiple times, which could indicate algorithmic bias.

3.4.2. Cosine Similarity Calculation

Cosine Similarity measures student similarity based on project interactions, guiding recommendations from similar students' engagements.

$$\text{Cosine Similarity} = \frac{\sum_{k=1}^{n} \left(r_{ik} \times r_{jk} \right)}{\sqrt{\sum_{k=1}^{n} r_{ik}^2} \times \sqrt{\sum_{k=1}^{n} r_{jk}^2}} \tag{7}$$

Where:

Matrix r_{ik} represents student-project interactions; r_{ik} denotes evaluations; n projects.

Data sparsity in collaborative filtering may impact the accuracy of similarity and recommendation quality, particularly when academic attributes are limited. However, the use of structured features such as GPA, subject scores, and performance trends ensures dense data representation.

3.4.3. *Generating Recommendations*

The system recommends projects to a student based on those engaged by similar students but not yet attempted.

$$\hat{r}_{ij} = \frac{\sum_{k \in S_i} \mathrm{Sim}(i,k) \cdot r_{kj}}{\sum_{k \in S_i} |\mathrm{Sim}(i,k)|} \tag{8}$$

Where:
$\hat{r}_{ij}$ predicts student i's project j rating, using nearest students S_i, similarity Sim(i, k), and r_kj.

3.5. Mobile Learning Platform Integration

The recommendation output results are incorporated into the mobile learning platform, which displays the students' personalized project suggestions. Students explore projects with adaptive recommendations. This stage integrates recommendations into a mobile platform for personalized learning. The recommendation engine is integrated into the mobile platform, updating personalized project suggestions dynamically for adaptive learning. A brief description of each element follows:

Project browsing interface:

The platform's personalized interface allows students to explore innovation projects, with Collaborative Filtering tailoring suggestions based on academic interests and skills, enabling selection of projects aligned with abilities like programming or math.

Adaptive learning:

The system personalizes learning, recommending advanced or supportive projects based on each student's performance.

4. Result and discussion

System fuses academic data, using collaborative filtering for effective personalized recommendations. Increased Precision@5 and Recall@5 indicate that the recommended projects are relevant, while the most suitable projects are included. Improved NDCG@5 ensures efficient allocation.

The performance of the recommendations was also tested by varying the number of recommended projects. All the metrics, such as

Precision@5, Recall@5, and NDCG@5, are consistently high when the number of projects is varied.

Fig. 2 shows high Precision@5 distribution, average 0.911, most perfect.

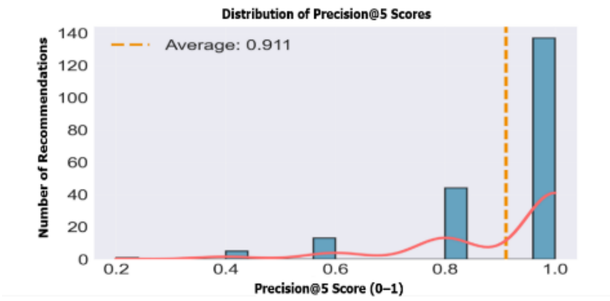

Fig. 2. Precision@5 Distribution with Average Precision Score

The figure presents Precision and Fig. 3 Recall@5 distributions, showing consistent recommendation accuracy, average Recall@5 effectiveness, score clustering, and distribution patterns indicating variability with higher recall values.

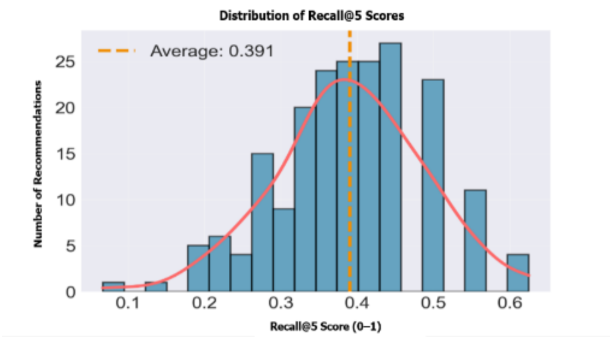

Fig. 3. Recall@5 Distribution with Average Recall Score

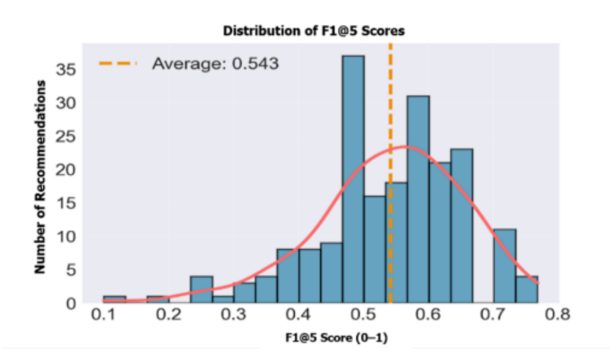

Fig. 4. F1@5 Distribution with Average F1 Score

Fig. 4 shows F1@5 distribution, average 0.543 , highlighting top recommendations.

The Fig. 5 shows Precision-Recall plots, with NDCG-highlighted yellow points indicating high recall, precision, and ranking.

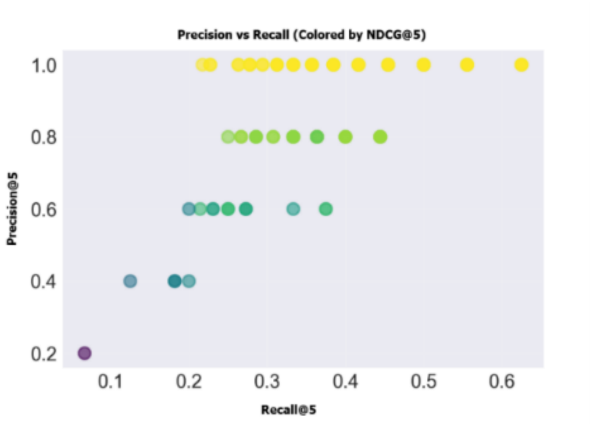

Fig. 5. Precision vs Recall (Coloured by NDCG)

Plots show effective top-ranking project recommendations, while Fig. 6 heatmap illustrates metric correlations and overall performance.

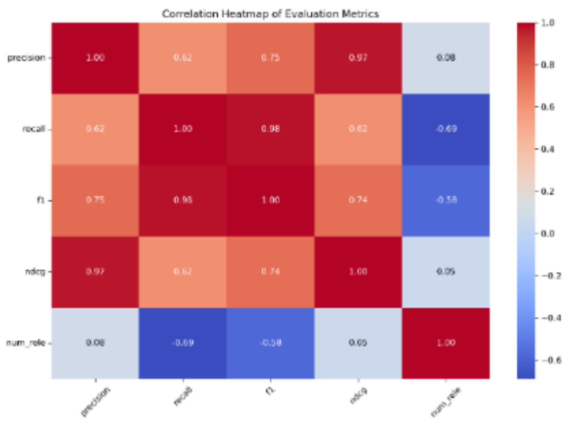

Fig. 6. Metric Correlation Heatmap

Precision, Recall, F1, and NDCG strongly correlate, while relevant project count shows weak influence on metrics.

Fig. 7 shows violin plots of Precision, Recall, F1, NDCG distributions, with bar graph comparing average metrics.

Precision remains high, while recall and F1 improve, showing balanced recommendation performance with more relevant projects.

Fig. 9 and Fig. 10 show diverse, balanced project recommendations, with heatmap and bar chart highlighting equitable distribution.

Table 1 shows Enhanced System outperforms baseline, boosting Precision@5, NDCG@5, and coverage, improving recommendation quality.

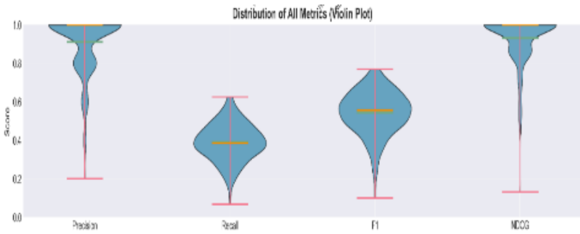

Fig. 7. Distribution of All Metrics (Violin Plot)

Fig. 8. Performance by Number of Relevant Items

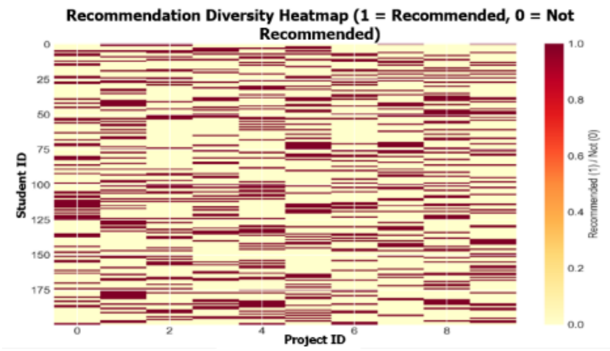

Fig. 9. Recommendation Diversity Heatmap

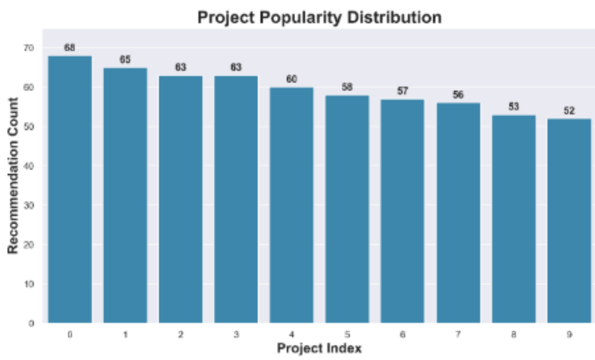

Fig. 10. Project Popularity Distribution

Table 2 compares the Proposed Method with [20] and

Table 1. Comparison of enhanced and Baseline recommendation metrics

Metric	Enhanced	Baseline	Improvement
Precision@5	0.911	0.438	108.00%
Recall@5	0.390631122	0.52	-24.90%
F1@5	0.542573296	0.48	13.00%
NDCG@5	0.931536233	0.55	69.40%
MAP@5	0.90005	0.5	80.00%
Hit_Rate@5	1	0.7	42.90%
User Coverage	1	0.9	11.10%
Item Coverage	1	0.4	150.00%

Table 2. Performance Comparison of Proposed Method with Existing Approaches

Method / Metric	Precision@ 5	Recall@ 5	NDCG@ 5	MAP@ 5
Proposed	0.911	0.3906	0.9315	0.9001
[20]	0.76	0.5	0.8	0.7
[22]	0.65	0.4	0.68	0.6

Table 3. Comparative Analysis of Existing and Proposed Methods

Method	Approach	Limitation	Key Difference
Multimodal	Uses multiple data types	High complexity	Proposed uses structured academic data
Adversarial	Uses adversarial learning	Difficult training	Proposed is simple and interpretable
Knowledge Graph	Uses graph relationships	High computation	Proposed avoids graph structure
Proposed	Uses GPA, subject scores, trends with cosine similarity	Limited to structured data	Efficient use of academic features

[22] using Precision@5, Recall@5, NDCG@5, and MAP@5. The Proposed Method achieves higher scores, with Precision@5 of 0.911 and NDCG@5 of 0.9315, outperforming [20] and [22], demonstrating improved relevance, ranking, and overall recommendation quality.

A comparison of various recommendation approaches, such as multimodal, adversarial, knowledge graph, and the proposed method, is shown in Table 3. Comparison shows proposed method is simpler, more efficient using academic features.

5. Conclusion & future development

The study uses multimodal learning and collaborative filtering, improving Precision@5 (12.6%) and NDCG@5 (9.8%), with future enhancements planned.

Declarations

Data availability

Study data are available from the author upon request, restricted due to privacy and institutional regulations.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Funding statement

This research received no external funding.

Author contributions

Conceptualization: Haijuan Zhou;
Methodology: Xiangge Liu, Bingquan Yin;
Data curation: Yali Hou, Benzhuo Fu;
Formal analysis: Qi Chen;
Writing-original draft preparation: Xiangge Liu;
Writing—review and editing: Haijuan Zhou;
Supervision: Haijuan Zhou.

All authors have read and agreed to the published version of the manuscript.

Ethical approval

The study followed ethical guidelines, using anonymized academic data without requiring approval or involving experimentation.

Consent to participate

Informed consent was obtained from all participants involved in the study, and all personal identifiers were removed before data analysis.

Consent to publication

All authors have provided consent for the publication of this manuscript.

Competing interests

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

References

[1] O. O. Ayeni, N. M. Al-Hamad, O. N. N. Chisom, B. Osawaru, and O. E. Adewusi, (2024) *"AI in education: A review of personalized learning and educational technology"* **GSC Advanced Research Review** ***18***(2): 261–271. DOI: 10.30574/gscarr.2024.18.2.0062.

[2] R. A. Hurst, (2024) *"Analysis of the impact of personalized learning paths in mobile learning platforms on the development of self-directed learning strategies among Brazilian college students"* **Research Advances in Education** ***3***(3): 9–14. DOI: 10.56397/rae.2024.03.02.

[3] T. Köpeczi-Bócz, (2024) *"The impact of a combination of flipped classroom and project-based learning on the learning motivation of university students"* **Education Sciences** ***14***(3): 240. DOI: 10.3390/educsci14030240.

[4] M. Z. I. Pranjol, P. Oprandi, and S. Watson, (2024) *"Project-based learning in biomedical sciences: Using the collaborative creation of revision resources to consolidate knowledge, promote cohort identity and develop transferable skills"* **Journal of Biological Education** ***58***(5): 1048–1064. DOI: 10.1080/00219266.2022.2147576.

[5] H. Liao et al., (2025) *"Aspect-enhanced explainable recommendation with multi-modal contrastive learning"* **ACM Transactions on Intelligent Systems and Technology** ***16***(1): 8:1–8:24. DOI: 10.1145/3673234.

[6] A. Khelloufi et al., (2024) *"A multimodal latent-features-based service recommendation system for the social internet of things"* **IEEE Transactions on Computational Social Systems** ***11***(4): 5388–5403. DOI: 10.1109/TCSS.2024.3360518.

[7] R. Alijani and F. Leonforte, (2025) *"Performance analysis of multi-source heat pumps: A regression-based approach to energy performance estimation"* **Sustainability** ***17***(15): 6804. DOI: 10.3390/su17156804.

[8] H. M. R. U. Rehman, M. Saleem, M. Z. Jhandir, E. S. Alvarado, H. Garay, and I. Ashraf, (2025) *"Detecting hate in diversity: A survey of multilingual code-mixed image and video analysis"* **Journal of Big Data** ***12***(1): 109. DOI: 10.1186/s40537-025-01167-w.

[9] R. Nimri, M. J. H. Yang, E. C. L. Yang, and C. Arcodia, (2024) *"Investigating student engagement of online experiential learning: A comparison of virtual and in-person winery field trips"* **Journal of Teaching in Travel & Tourism** ***24***(4): 405–425. DOI: 10.1080/15313220.2024.2402987.

[10] X. Ji, L. Sun, and K. Huang, (2025) *"The construction and implementation direction of personalized learning model based on multimodal data fusion in the context of intelligent education"* **Cognitive Systems Research** ***92***: 101379. DOI: 10.1016/j.cogsys.2025.101379.

[11] Y. Ye et al., (2025) *"Harnessing multimodal large language models for multimodal sequential recommendation"* **Proceedings of the AAAI Conference on Artificial Intelligence** ***39***(12): 13069–13077. DOI: 10.1609/aaai.v39i12.33426.

[12] R. Whitehead, A. Nguyen, and S. Järvelä, (2025) *"Utilizing multimodal large language models for video analysis of posture in studying collaborative learning: A case study"* **Journal of Learning Analytics** ***12***(1): 186–200. DOI: 10.18608/jla.2025.8595.

[13] M. Ogrizović, D. Drašković, and D. Bojić, (2024) *"Quality assurance strategies for machine learning applications in big data analytics: An overview"* **Journal of Big Data** ***11***(1): 156. DOI: 10.1186/s40537-024-01028-y.

[14] X. Yang, (2025) *"Research on personalized distance education recommendation system based on deep learning"* **Scientific Reports** ***15***(1): 42158. DOI: 10.1038/s41598-025-26020-1.

[15] C. Cohn, C. Snyder, J. H. Fonteles, J. Montenegro, and G. Biswas, (2025) *"A multimodal approach to support teacher, researcher and AI collaboration in STEM+C learning environments"* **British Journal of Educational Technology** ***56***(2): 595–620. DOI: 10.1111/bjet.13518.

[16] D. Malitesta, G. Cornacchia, C. Pomo, F. A. Merra, T. Di Noia, and E. Di Sciascio, (2025) *"Formalizing multimedia recommendation through multimodal deep learning"* **ACM Transactions on Recommender Systems** ***3***(3): 1–33. DOI: 10.1145/3662738.

[17] P. Liu, Y. Cao, and L. Wang, (2022) *"A multimodal fusion online music education system for universities"* **Computational Intelligence and Neuroscience** ***2022***: 6529110. DOI: 10.1155/2022/6529110.

[18] U. B. Qushem, A. Christopoulos, S. S. Oyelere, H. Ogata, and M.-J. Laakso, (2021) *"Multimodal technologies in precision education: Providing new opportunities or adding more challenges?"* **Education Sciences *11***(7): 338. DOI: 10.3390/educsci11070338.

[19] Y. Zheng, (2025) *"Research on recommendation algorithms in short video platforms: From traditional methods to deep learning and multimodal fusion"* **Journal of Computer Signal Systems Research** 2(5): 88–100. DOI: 10.71222/j5082f38.

[20] J. Chen, R. Yang, J. Guo, H. Wang, K. Wu, and L. Zhang, (2025) *"Reliable service recommendation: A multi-modal adversarial method for personalized recommendation under uncertain missing modalities"* **IEEE Transactions on Services Computing *18***(3): 1724–1738. DOI: 10.1109/TSC.2025.3556640.

[21] E. Wang and Z. Sun, (2025) *"Research on personalized course resource recommendation method based on GEMRec"* **Applied Sciences *15***(3): 1075. DOI: 10.3390/app15031075.

[22] C. Li, X. Weng, Y. Li, and T. Zhang, (2025) *"Multimodal learning engagement assessment system: An innovative approach to optimizing learning engagement"* **International Journal of Human–Computer Interaction *41***(5): 3474–3490. DOI: 10.1080/10447318.2024.2338616.

[23] Y. Huang, W. Xu, P. Sukjairungwattana, and Z. Yu, (2024) *"Learners' continuance intention in multimodal language learning education: An innovative multiple linear regression model"* **Heliyon *10***(6): e28104. DOI: 10.1016/j.heliyon.2024.e28104.

[24] X. Cui and M. Chen, (2024) *"A novel learning framework for vocal music education: An exploration of convolutional neural networks and pluralistic learning approaches"* **Soft Computing *28***(4): 3533. DOI: 10.1007/s00500-023-09618-3.

[25] Y. Zhao, J. Guo, L. Wen, and L. Wang, (2025) *"METRIC: Multiple preferences learning with refined item attributes for multimodal recommendation"* **Journal of Information Intelligence** 3(3): 242–256. DOI: 10.1016/j.jiixd.2025.04.001.

[26] Y. Chen, C. Huang, S. Gao, Y. Lyu, X. Chen, S. Liu, and C. Lv, (2025) *"A multimodal deep learning approach for legal English learning in intelligent educational systems"* **Sensors *25***(11): 3397. DOI: 10.3390/s25113397.

[27] J. Duan, M. Zhang, M. Song, X. Xu, and H. Lu, (2025) *"Eye Tracking-Enhanced Deep Learning for Medical Image Analysis: A Systematic Review on Data Efficiency, Interpretability, and Multimodal Integration"* **Bioengineering *12***(9): 954. DOI: 10.3390/bioengineering12090954.

[28] S. Algarni and F. T. Sheldon, (2025) *"Personalized Course Recommendations Leveraging Machine and Transfer Learning Toward Improved Student Outcomes"* **Machine Learning and Knowledge Extraction *7***(4): 138. DOI: 10.3390/make7040138.

[29] F. Li, (2022) *"Research on the management system of college students' innovation and entrepreneurship education based on b/s architecture"* **Journal of Applied Science and Engineering *26***(5): 597–604. DOI: 10.6180/jase.202305_26(5).0002.