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A HYBRID AI-BASED COURSE RECOMMENDATION MODEL FOR DOST USING SENTIMENT-AWARE LEARNING

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ABSTRACT

The rapid expansion of interdisciplinary undergraduate programs has increased the complexity of academic decision-making among higher education aspirants. Although centralized admission platforms simplify institutional admission procedures, they often lack intelligent academic guidance systems capable of assisting students in selecting suitable academic programs aligned with their abilities, interests, and career goals. The Degree Online Services Telangana (DOST) platform provides a unified admission environment for undergraduate programs in Telangana State. However, the present admission process mainly focuses on administrative automation and does not support personalized course recommendation.

This study presents a hybrid artificial intelligence-based recommendation model for undergraduate course selection within the DOST ecosystem. The proposed model combines collaborative filtering, latent factor learning, and sentiment-aware analysis to generate personalized course recommendations. Academic performance indicators, contextual attributes, peer influence patterns, and qualitative feedback representations are integrated to estimate recommendation suitability scores. Mathematical formulations for similarity computation, latent interaction learning, recommendation fusion, and optimization are incorporated to establish a theoretically grounded recommendation architecture.

A preliminary validation study based on survey observations highlights the necessity of intelligent recommendation support mechanisms within centralized admission environments. The proposed model provides a theoretically grounded approach for integrating academic performance, contextual attributes, and sentiment-aware learning into undergraduate course recommendation. The study contributes a domain-specific recommendation architecture for the DOST ecosystem and offers a foundation for subsequent empirical evaluation and large-scale deployment.

Index Terms: Recommender Systems, DOST, Sentiment Analysis, Collaborative Filtering, Educational Data Mining, Machine Learning

1. INTRODUCTION

The growing diversity of undergraduate academic programs has significantly increased the complexity of course selection among higher education aspirants. Emerging disciplines such as artificial intelligence, data science, cybersecurity, and business analytics have transformed conventional undergraduate education into a multidimensional academic environment [1]. While these developments expand educational opportunities, they also create uncertainty among students who often lack sufficient awareness regarding academic suitability, employability trends, and long-term career implications.

To simplify undergraduate admissions, the Government of Telangana introduced the Degree Online Services Telangana (DOST) platform, which centralizes the admission process across affiliated colleges and universities. The platform successfully reduces administrative complexity and streamlines seat allocation procedures. However, the current admission mechanism primarily focuses on registration and option-entry activities and does not provide intelligent academic guidance during course selection. As a result, students frequently depend on peer influence, incomplete information, or social trends while selecting academic programs, which may lead to inappropriate academic choices and reduced career alignment.

Recent advancements in recommender systems have demonstrated their effectiveness in supporting personalized decision-making across multiple domains, including healthcare, e-commerce, entertainment, and education [2]. Educational recommender systems have been used to suggest learning resources, predict student preferences, and support academic planning [3]. Collaborative filtering approaches identify behavioral similarities among users, whereas content-based approaches utilize feature-level representations to generate recommendations [4]. However, traditional recommendation systems primarily focus on quantitative interactions and often neglect qualitative indicators such as institutional perception, student satisfaction, and experiential feedback.

Simultaneously, sentiment-aware learning and natural language processing have emerged as powerful approaches for extracting semantic information from textual data [5]. Transformer-based architectures such as Bidirectional Encoder Representations from Transformers (BERT) have significantly improved contextual understanding in sentiment classification tasks [6]. Integrating sentiment-oriented analysis within educational recommender systems enables the incorporation of real-world opinions and satisfaction indicators into recommendation generation.

Despite significant progress in recommendation methodologies, limited research has specifically focused on centralized undergraduate admission ecosystems such as DOST, where course selection decisions involve multiple academic, social, and contextual factors. Motivated by this research gap, the present study introduces a hybrid recommendation model that combines collaborative filtering, latent factor learning, and sentiment-aware analysis for personalized undergraduate course recommendation within DOST.

II. RELATED WORK

Educational recommender systems have evolved considerably over the past decade due to increasing demand for intelligent academic guidance and personalized learning support. Existing studies mainly focus on collaborative filtering, content-based recommendation, and hybrid recommendation techniques to support academic planning and course recommendation.

Collaborative filtering methods identify similarities among users based on historical interaction patterns [7]. These approaches have demonstrated strong performance in recommendation environments with sufficient interaction data. However, educational environments frequently suffer from sparse datasets and cold-start problems, which reduce the effectiveness of purely collaborative approaches [8].

Content-based recommendation systems attempt to address these limitations by utilizing feature-level similarities between users and items. Such approaches consider attributes including academic performance, institutional characteristics, learning interests, and course prerequisites [9]. Although content-based methods improve contextual relevance, they often fail to capture dynamic social and behavioral influences associated with academic decision-making.

Hybrid recommendation models combine multiple recommendation techniques within a unified architecture to improve prediction accuracy and recommendation diversity [10]. Previous studies indicate that hybrid systems significantly outperform standalone recommendation approaches in educational environments [11].

Machine learning and deep learning methodologies have further enhanced recommendation capabilities through latent representation learning. Matrix factorization techniques have been extensively utilized to discover hidden relationships between users and items using low-dimensional feature representations [12]. Neural collaborative filtering models additionally learn nonlinear interaction patterns between users and recommendation targets [13].

Recent developments in sentiment analysis have expanded recommendation capabilities through extraction of semantic and emotional information from textual feedback [14]. Transformer-based language models such as BERT have improved contextual sentiment classification by capturing bidirectional linguistic relationships [15]. Integrating sentiment-aware mechanisms within recommendation systems improves contextual understanding and enables inclusion of qualitative feedback representations.

Although considerable research has been conducted on educational recommender systems, limited studies have addressed recommendation support within centralized admission platforms such as DOST. Existing systems generally overlook the combined influence of academic performance, peer preference, geographical accessibility, institutional perception, and sentiment-oriented feedback during undergraduate course selection. Consequently, there remains a need for intelligent recommendation models specifically tailored to centralized educational admission ecosystems.

III. PROBLEM FORMULATION AND SYSTEM MODEL

The developed recommendation model formulates undergraduate course selection as a personalized ranking and prediction problem. Let $U=\{u_1,u_2,u_3,\ldots,u_m\}$ represent the set of students, and $C=\{c_1,c_2,c_3,\ldots,c_n\}$ represent the set of available undergraduate courses within the DOST platform.

The objective of the model is to estimate the suitability score between a student u_i and a course c_j using academic, contextual, behavioural, and sentiment-oriented information.

3.1 Student Feature Representation

Each student is represented using a multidimensional feature vector $X_u=[a_1,a_2,\ldots,a_p,g,l,s_p]$ where a_1 ,$a_2,\ldots,a_p$ represent subject-wise academic scores, g denotes academic group information, l represents geographical location encoding, s_p denotes peer influence score.

The feature vector captures both academic capability and contextual characteristics associated with the student.

3.2 Course Feature Representation

Each course is represented as $Y_c = [d, r, t, s_c]$ where d represents domain relevance, r denotes institutional ranking, t indicates course trend score, s_c represents sentiment score. The trend score reflects emerging market demand associated with specific courses.

3.3 Similarity Modelling

To identify students with comparable academic and behavioural characteristics, cosine similarity is employed

$$Sim(u_i,u_j)=\frac{\sum_{k=1}^{n} X_{ik}X_{jk}}{\sqrt{\sum_{k=1}^{n} X_{ik}^2}\sqrt{\sum_{k=1}^{n} X_{jk}^2}} \quad (1)$$

Cosine similarity is used because it effectively measures directional similarity between multidimensional feature vectors while reducing the impact of magnitude variations.

The neighbourhood set of student (u_i) is defined as

$$N(u_i)=\{u_j \in U \mid Sim(u_i, u_j)>\theta\} \quad (2)$$

where θ denotes the similarity threshold.

3.4 Collaborative Recommendation Score

The collaborative recommendation score is computed using weighted neighbourhood aggregation

$$CF(u_i, c_j)=\frac{\sum_{u_k \in N(u_i)} Sim(u_i, u_k).R_{kj}}{\sum_{u_k \in N(u_i)} |Sim(u_i, u_k)|} \quad (3)$$

Where R_{kj} denotes the interaction or rating of student u_k for course c_j. This formulation estimates recommendation suitability using neighbouring student preferences and interaction behaviour.

3.5 Latent Factor Learning

To capture hidden relationships between students and courses, matrix factorization is utilized. The interaction matrix is approximated as $R \approx PQ^T$

Where $P \in R^{m\,X\,k}$ represents latent student embedding's, $Q \in R^{n\,X\,k}$ represents latent course embedding's, k denotes latent dimensionality. The predicted interaction score is defined as

$$\widehat{R_{ij}} = \mu + b_i + b_j + P_i^T Q_j \quad (4)$$

Where μ denotes the global interaction mean, b_i and b_j represent user and course bias terms. Latent factor learning enables the model to identify implicit relationships between students and academic programs.

3.6 Sentiment-Aware Learning

Sentiment-aware learning is performed using normalized polarity estimation

$$S(c_j)=\frac{N_{pos}-N_{neg}}{N_{pos}+N_{neg}+N_{neu}} \quad (5)$$

Where N_{pos} represents positive feedback instances, N_{neg} represents negative feedback instances, N_{neu} represents neutral feedback instances. The sentiment score represents the overall perception associated with course c_j .

3.7 Hybrid Recommendation Function

The final recommendation score is computed as

$$F(u_i , c_j)= \alpha . CF(u_i, c_j)+ \beta . \widehat{R_{ij}} + \gamma . S(c_j) \quad (6)$$

subject to

$$\alpha+\beta+\gamma=1$$

where α,β,γ denote weighting coefficients controlling contribution of collaborative filtering, latent interaction learning, and sentiment-aware analysis.

The hybrid recommendation formulation improves recommendation robustness by integrating quantitative and qualitative information.

3.8 Optimization Objective

The recommendation model minimizes regularized prediction error

$$\min_{P,Q} \sum_{(i,j)\epsilon K} \left(R_{ij} - \hat{R}_{ij}\right)^2 + \lambda \left(\| P_i \|^2 + \| Q_j \|^2\right) \quad (7)$$

Where K represents observed interactions, λ denotes the regularization parameter. Regularization minimizes overfitting and improves model generalization capability.

3.9 Ranking Mechanism

Courses are ranked according to descending recommendation scores

$$\text{TopN}(u_i)=\arg\max_{c_j \in C} F(u_i,c_j) \quad (8)$$

The system finally recommends the highest-ranked courses to students during DOST option selection.

IV. PROPOSED ARCHITECTURE AND RECOMMENDATION WORKFLOW

The proposed recommendation model follows a multilayer architecture designed to integrate structured academic information with unstructured sentiment-oriented feedback. The architecture consists of interconnected modules responsible for data acquisition, preprocessing, sentiment extraction, recommendation generation, and ranking.

4.1 Data Acquisition Layer

The first layer collects student-specific attributes including academic records, subject-wise marks, educational background, geographical information, and peer preference indicators. Simultaneously, textual feedback associated with courses and institutions is collected from students and faculty members.

The overall dataset is represented as

$$D = \left\{\left(u_i, c_j, r_{ij}, f_{ij}\right) \mid u_i \epsilon\, U, c_j \epsilon\, C\right\} \quad (9)$$

where u_i denotes student i, c_j denotes course j, r_{ij} represents interaction score, f_{ij} represents feedback information.

4.2 Data Preprocessing Layer

The preprocessing module performs normalization, cleaning, feature extraction, and encoding operations. Numerical attributes are normalized using min-max normalization

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (10)$$

where x represents original feature value, x′ denotes normalized value. Textual feedback is processed using tokenization, stop-word removal, and contextual representation learning.

4.3 Sentiment Analysis Layer

The sentiment analysis module converts textual feedback into contextual sentiment representations. Transformer-based models are employed to capture semantic relationships within feedback text.

The sentiment probability distribution is computed using Softmax activation

$$P(y_i)=\frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}} \quad (11)$$

Where $P(y_i)$ denotes probability of sentiment class i, K represents total sentiment classes. Positive and negative sentiment probabilities are used to compute normalized sentiment scores associated with individual courses.

4.4 Hybrid Recommendation Engine

The recommendation engine integrates collaborative filtering scores, latent interaction representations, and sentiment-aware information computed in Section 3.

The hybrid recommendation score is represented as

$$F(u_i,c_j)=\alpha CF(u_i,c_j)+\beta\widehat{R_{ij}}+\gamma S(c_j) \quad (12)$$

The integrated recommendation strategy improves personalization capability by combining behavioural similarity, latent preference learning, and qualitative feedback representations.

4.5 Recommendation and Ranking Layer

The final recommendation list is generated by ranking courses according to descending recommendation scores

$$TopN(u_i) = \underset{c_j\in C}{\arg\max} F\,(u_i,c_j) \quad (13)$$

The ranked recommendation list is presented to students during DOST option selection.

V. PRELIMINARY VALIDATION AND EVALUATION FRAMEWORK

The proposed recommendation model was preliminarily validated through a survey-based study conducted to understand the challenges faced by students during undergraduate course selection. The objective was to identify factors influencing academic decision-making and to assess the need for intelligent recommendation support within the DOST admission ecosystem.

5.1 Survey Design and Data Collection

A structured questionnaire was administered among undergraduate aspirants and faculty members associated with the admission process. The survey focused on identifying major factors influencing course selection, awareness regarding emerging academic programs, peer influence, institutional preferences, and perceived limitations of the existing DOST admission process. A total of **120 undergraduate students** and **15 faculty members** participated in the survey.

The questionnaire consisted of five sections:

1. Academic awareness and course knowledge
2. Influence of peer groups and family
3. Awareness of career opportunities
4. Institutional preference factors
5. Satisfaction with existing admission guidance mechanisms

Table 1. Survey Participants

Category	Number of Participants
Undergraduate Students	120
Faculty Members	15
Total Participants	135

5.2 Survey Findings

The collected responses revealed several challenges associated with undergraduate course selection.

Table 2. Major Factors Influencing Course Selection

Factor	Percentage (%)
Career Opportunities	82
Peer Influence	68
Family Suggestions	61
Institutional Reputation	74
Personal Interest	79

The results indicate that career opportunities and personal interest are the primary factors influencing course selection decisions. However, a considerable proportion of students reported depending on peer influence and external opinions while selecting courses.

Table 3. Challenges Identified During Course Selection

Challenge	Percentage (%)
Lack of Academic Guidance	71
Limited Awareness of Emerging Courses	66
Uncertainty About Career Outcomes	64
Dependence on Peer Suggestions	68
Difficulty Comparing Courses	59

The findings demonstrate that students often encounter uncertainty when selecting academic programs. Many participants indicated limited awareness regarding interdisciplinary courses such as Artificial Intelligence, Data Science, Cyber Security, and Business Analytics.

5.3 Need for Intelligent Recommendation Support

Survey responses suggest that the current admission process effectively manages administrative operations but provides limited support for academic decision-making.

Approximately:

- **78% of students** expressed interest in receiving personalized course recommendations.
- **72% of faculty members** agreed that intelligent recommendation systems could improve course selection quality.
- **69% of respondents** believed that data-driven guidance would reduce inappropriate course selection.

These observations highlight the need for recommendation systems capable of integrating academic performance, contextual information, student interests, and experiential feedback.

5.4 Evaluation Metrics

Future implementation of the recommendation model may be evaluated using standard recommender system performance metrics.

Precision measures the proportion of relevant recommendations among the generated recommendations.

$$\text{Precision}=\frac{TP}{TP+FP} \tag{14}$$

Recall measures the capability of the system to retrieve relevant recommendation instances.

$$\text{Recall}=\frac{TP}{TP+FN} \tag{15}$$

F1-score provides a balanced evaluation of recommendation effectiveness.

$$\text{F1}=2 \text{ X } \frac{Precision\ X\ Recall}{Precision+Recall} \tag{16}$$

RMSE measures prediction accuracy by comparing actual and predicted recommendation scores.

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_i - \widehat{R_i})^2} \tag{17}$$

Where R_i represents actual interaction values, $\widehat{R_i}$ denotes predicted recommendation scores, N indicates total observations.

5.4 Discussion of Validation Results

The survey findings demonstrate a substantial demand for intelligent academic guidance during undergraduate admissions. Students frequently rely on peer influence, incomplete information, and subjective opinions while selecting academic programs. Such practices may lead to inappropriate course choices and reduced alignment between academic capabilities and career aspirations.

The proposed recommendation model addresses these challenges by integrating:

- Academic performance indicators
- Contextual attributes
- Peer influence patterns
- Institutional information
- Sentiment-aware feedback analysis

The integration of these factors provides a more comprehensive decision-support mechanism compared with conventional admission guidance approaches.

5.6 Future Experimental Evaluation

Future work will focus on implementing the proposed recommendation model using large-scale institutional admission datasets collected from centralized admission systems and affiliated colleges. The implementation phase will involve the construction of student-course interaction matrices, transformer-based sentiment classification, hyperparameter optimization, and comparative performance evaluation.

The proposed model will be evaluated against established recommendation techniques, including Collaborative Filtering, Content-Based Recommendation, Matrix Factorization, and Neural Collaborative Filtering. Standard evaluation metrics such as Precision, Recall, F1-Score, and RMSE will be employed to assess recommendation accuracy, ranking effectiveness, scalability, and personalization capability.

6. DISCUSSION AND RESEARCH CONTRIBUTIONS

The increasing complexity of undergraduate admissions has created a strong need for intelligent academic guidance systems capable of supporting personalized educational decision-making. Existing centralized admission platforms primarily focus on administrative automation while providing limited analytical assistance during course selection.

The proposed work addresses this challenge by integrating collaborative recommendation mechanisms, latent interaction learning, and sentiment-aware analysis within a unified educational recommendation model. Unlike conventional recommendation systems that primarily depend on historical interaction data, the proposed approach incorporates multidimensional contextual information including academic performance, geographical accessibility, peer influence, institutional perception, and qualitative feedback representations.

One of the major contributions of this study lies in the integration of sentiment-aware learning into undergraduate course recommendation within centralized admission ecosystems. Traditional educational recommender systems often neglect qualitative indicators associated with user satisfaction and institutional perception. Incorporating sentiment-oriented information improves contextual understanding and recommendation personalization.

Another important contribution involves latent factor learning for identifying implicit relationships between students and academic programs. Matrix factorization enables the recommendation model to discover hidden preference structures that may not be directly observable through explicit academic information.

The proposed hybrid recommendation strategy additionally reduces limitations associated with standalone collaborative filtering approaches, particularly sparsity and cold-start problems frequently encountered in educational datasets.

Despite its contributions, the present study has certain limitations. The work primarily focuses on conceptual modeling and theoretical formulation rather than large-scale implementation. The absence of institutional-scale datasets limits experimental evaluation and comparative benchmarking.

Future research may extend the recommendation model through integration of graph-based learning, deep neural recommendation architectures, labor-market analytics, and real-time adaptive recommendation mechanisms.

7. CONCLUSION

This study presented a hybrid artificial intelligence-based recommendation model for undergraduate course selection within the Degree Online Services Telangana (DOST) ecosystem. The proposed model integrates collaborative filtering, latent factor learning, and sentiment-aware analysis to support personalized academic decision-making in centralized admission environments.

Unlike traditional recommendation approaches that primarily rely on historical interaction patterns, the developed recommendation model incorporates multidimensional information including academic performance, contextual characteristics, peer influence, institutional perception, and qualitative feedback representations.

The mathematical formulation and hybrid recommendation strategy provide a theoretically grounded recommendation architecture capable of modeling both explicit and implicit student-course relationships. Furthermore, the multilayer architecture improves modularity, adaptability, and scalability for future implementation within large-scale educational admission systems.

Preliminary survey-based observations indicate the necessity of intelligent recommendation support systems for undergraduate admissions, particularly in environments where students experience uncertainty regarding academic program selection.

The proposed recommendation architecture provides a scalable foundation for intelligent academic decision support within centralized admission ecosystems. Future work will focus on large-scale implementation, empirical validation, and comparative evaluation using institutional admission datasets.

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