

Personalised E-Learning Course Recommendation System

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ABSTRACT

The Personalised E-Learning Course Recommendation System was created to improve the learning experience by offering customised course suggestions based on user preferences. The system looked at inputs like university name, course difficulty level, and user rating to recommend the top 10 most relevant courses. It used Natural Language Processing (NLP) techniques for similarity matching. Each recommended course included details such as the course name, skills covered, description, and a direct URL for easy access. The project included important modules like New User Sign-Up, User Login, and Course Recommendation, which made a user-friendly interface for learners. Users entered their preferences, and the system filtered and ranked courses based on similarity scores from the dataset features. The system was built using Python 3.7.2 with a MySQL database. Instead of real-time web scraping or external APIs, the project used a prepared dataset to simulate recommendations. This demonstrated how smart academic advising systems can support personalised learning pathways.

Keywords: Personalised Recommendation System, E-Learning, Course Recommendation, Natural Language Processing (NLP), Machine Learning, Hybrid Filtering, Content-Based Filtering, Collaborative Filtering, TF-IDF Vectorisation, Cosine Similarity, User Profiling, Learning Analytics.

I. INTRODUCTION

In recent years, the rapid growth of online learning platforms has changed education significantly. These platforms offer thousands of courses, making education more accessible, flexible, and inclusive for learners around the world. This digital growth has enabled people to acquire new skills, no matter their location or financial situation. However, the sheer number of available courses has also caused information overload. Learners often have a hard time finding courses that fit their interests, academic background, and career goals, resulting in wasted time and less engagement.

To tackle this problem, a Personalised E-Learning Course Recommendation System was created to help learners find suitable courses. The system looks at user preferences, profiles, and ratings to suggest relevant options. By using methods like content-based filtering and collaborative filtering, the system generates tailored recommendations. These systems improve learning efficiency, boost user satisfaction, and help learners locate appropriate educational resources more effectively.

II. RELATED WORK

E-learning recommender systems use collaborative, content-based, and hybrid methods.

AI approaches tackle issues like data sparsity, privacy, and transparency [1].

An autoencoder-based collaborative filtering model for e-learning recommendations performs better than KNN, SVD, SVD++, and NMF in predicting learner preferences and improving accuracy [2].

A hybrid recommender combines TF-IDF, SBERT, and regression models. SBERT, paired with Gradient Boosting, enhances accuracy and reliability across various datasets [3].

E. Ilkou, A. Hotho, et al. (2021). EduCOR: An Educational and Career-Oriented Recommendation Ontology. Springer Nature uses high computational resources, making it less suitable for lightweight academic systems [4].

Intelligent recommendation algorithms and learning analytics incorporate data mining and hybrid techniques to personalise learning paths. This approach boosts adaptability, engagement, and outcomes in e-learning [5].

Federated collaborative filtering allows on-device training without sharing data. It maintains accuracy similar to traditional methods while significantly improving user privacy in recommendations [6].

UPRec includes user attributes and social graphs in pre-training with self-supervised tasks. This improves personalisation and surpasses traditional recommendation models on large-scale datasets [7].

FEBR is an expert-based framework using apprenticeship learning to enhance recommendation quality. It ensures reliability, personalisation, and transparency while keeping user engagement through ethical recommendation practices [8].

E-learning struggles with information overload. This study employs an autoencoder-based collaborative filtering model to predict preferences, outperforming KNN, SVD, SVD++, and NMF with better accuracy and efficiency [9].

E-learning addresses information overload by applying recommender systems and data mining techniques. This delivers personalised, high-quality learning materials tailored to each student's needs [10].

A text mining-based video recommender system connects job skills with learning content. It improves personalisation and achieves 82.8% useful recommendations for better learning experiences [11].

An interactive educational recommender system allows users control over input, process, and output. This enhances transparency, trust, and satisfaction in personalised learning experiences [12].

The Outcome-Based Educational Recommender System (OBER) suggests learning resources aligned with desired outcomes. This approach boosts personalisation, guides students toward goal-oriented learning paths, and improves educational effectiveness [13].

Personalised learning recommendation systems from 2013 to 2023 examine learner modelling, algorithms, and challenges. They highlight future directions to tackle information overload in e-learning environments [14].

A hybrid POA, Apriori, and MR-CNN model offers scalable e-learning recommendations. It enhances accuracy, robustness, and performance compared to traditional methods using large-scale datasets [15].

S.NO	Title	Problem Statement	Methodology used	Limitations
1	Recommender Systems in E-Learning: Trends, Challenges, and Future Directions.	Difficulty in handling personalisation and scalability in e-learning systems.	Survey of CF, CBF, hybrid, and AI-based models.	Data sparsity, cold start, privacy issues.
2	Personalised E-Learning Recommender System Based on Autoencoders.	Low accuracy in traditional recommendation methods.	Autoencoder-based collaborative filtering.	Requires large data and computational cost.
3	AI-Driven Hybrid Recommender Framework.	Ineffective personalisation in standalone systems.	Hybrid model using TF-IDF, SBERT, and regression.	Computational complexity, dataset dependency.
4	EduCOR Ontology Framework.	Lack of unified representation for learning resources.	Ontology-based recommendation system.	Complex design, maintenance overhead.
5	Intelligent Recommendation Algorithms in E-Learning.	Need for adaptive and personalised learning paths.	Hybrid recommendation + learning analytics.	High data dependency, system complexity.
6	Federated Collaborative Filtering.	Privacy risks in centralised recommendation systems.	Federated learning with collaborative filtering.	Communication overhead, slower training.
7	UPRec: User-Aware Pre-training.	Poor personalisation in pre-trained models.	User-aware self-supervised learning.	Requires large-scale datasets.
8	FEBR Framework.	Difficulty in evaluating content quality in recommendations.	Apprenticeship learning with expert policy.	Complex implementation, expert dependency.
9	Autoencoder-Based Recommendation.	Inefficiency of traditional filtering techniques	Deep learning autoencoder models.	High computational resources.
10	Multimedia-Based E-Learning Recommender.	Limited use of multimedia data in recommendations.	Multimedia-based recommendation system.	Data heterogeneity issues.
11	Skill-Based Video Recommendation.	Difficulty matching videos to user skills.	Skill-based filtering approach.	Limited adaptability.
12	User-Controlled Educational Recommender.	Lack of user control in recommendation systems.	Interactive user-driven recommendation.	User bias, complexity.
13	Outcome-Based Educational Recommender (OBER).	Misalignment with learning outcomes.	Outcome-based recommendation approach.	Limited generalisation.

14	Personalised Learning Recommendation Study.	Need for improved personalisation techniques.	Comparative analysis of recommendation models.	Lacks real-time implementation.
15	Deep Learning-Based Distance Education Recommender.	Inefficiency in distance learning recommendations.	Deep learning-based system.	High computational cost.

III. METHODOLOGY

System Architecture

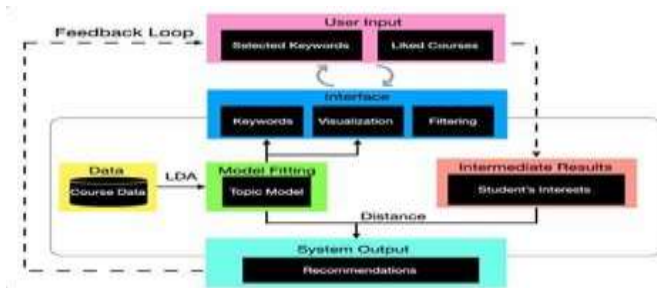


Figure: 3.1

Figure 3.1 shows a recommendation system workflow. User input, which includes selected keywords and liked courses, is processed through an interface that involves keyword analysis, visualisation, and filtering. Data from course datasets is modelled using LDA topic modelling. Intermediate results identify student interests. The system then generates personalised course recommendations and includes a feedback loop for improvement.

Algorithm

Step 1: Start

Initialise the system.

Step 2: User Login

The user enters a username and password.
The system validates the credentials using the database.
If the credentials are valid, access is granted.

Otherwise, an error message is displayed, and the process stops.

Step 3: Accept User Input

Collect user preferences such as keywords and previously liked courses.
Store this input for further processing.

Step 4: Data Processing

Retrieve course data from the dataset or database.
Perform preprocessing steps such as cleaning and filtering the data.

Step 5: Model Processing

Apply topic modelling techniques (e.g., LDA).
Extract relevant features and keywords.
Compute similarity between user preferences and course data.

Step 6: Generate Recommendations

Rank courses based on similarity scores.
Select the top N relevant courses.
Display the recommended courses to the user.

Step 7: Feedback Loop

Collect user feedback (likes or dislikes).
Update the user profile to improve future recommendations.

Step 8: Logout

Prompt the user to log out.
If confirmed, terminate the session.

Step 9: End

Stop the system.

IV. RESULT ANALYSIS



This personalised e-learning system suggests suitable courses based on user interests, improving learning efficiency by analysing preferences, behaviour, and skills to deliver tailored recommendations.

The Personalised E-Learning Course Recommendation System was evaluated to assess its effectiveness in providing accurate and relevant recommendations. The system integrates multiple recommendation approaches:

- Content-Based Filtering
- Collaborative Filtering
- Deep Learning-Based Recommendation
- Proposed Hybrid Model (Content + Collaborative + NLP Similarity)

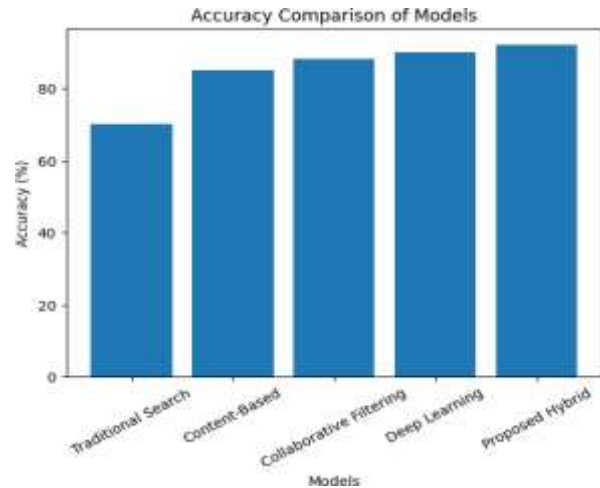
The evaluation was conducted using standard performance metrics:

- Accuracy
- Precision
- Recall
- F1-Score

Evaluation Metrics

Accuracy

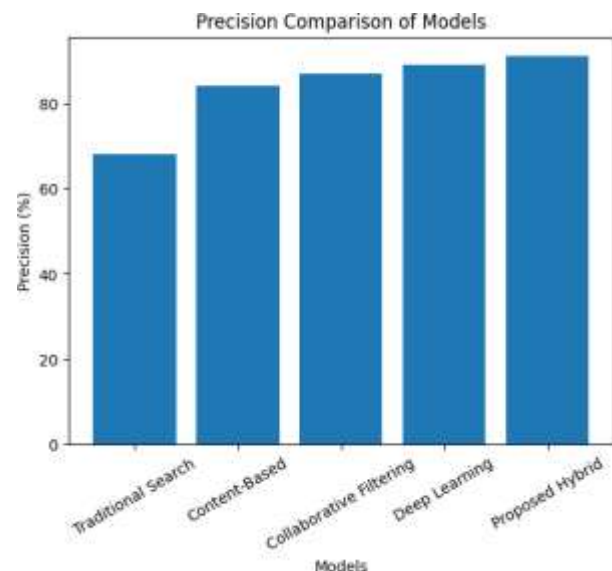
Measures the overall correctness of recommendations.



The results indicate that the hybrid model achieves the highest accuracy (approximately 92%), outperforming deep learning models (around 90%), collaborative filtering (about 88%), content-based filtering (around 85%), and traditional search methods (approximately 70%).

Precision

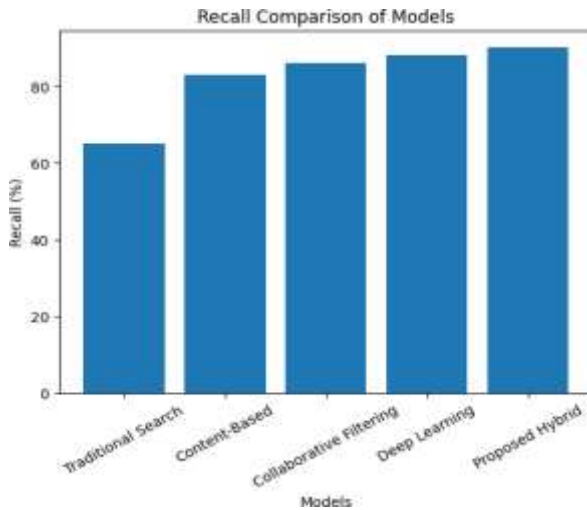
Precision measures how many of the recommended courses are actually relevant.



The hybrid model achieves the highest precision (around 91–92%), followed by deep learning (approximately 89%), collaborative filtering (around 87%), content-based filtering (about 84%), and traditional search (around 68–70%).

Recall

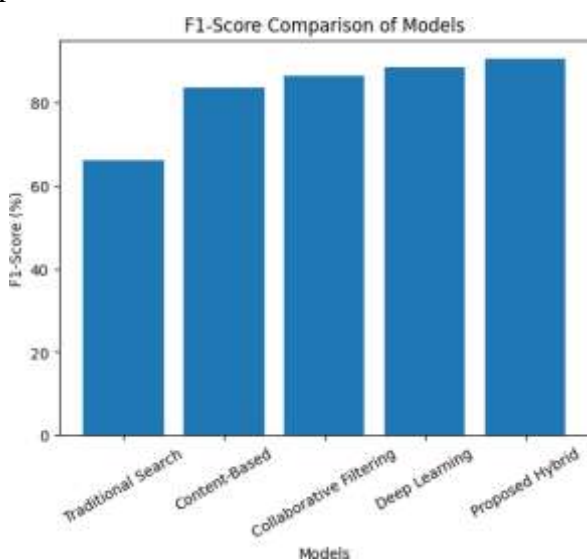
Recall measures how effectively the system identifies all relevant courses.



The hybrid model again performs best, achieving recall values of approximately 90–91%, followed by deep learning (around 88%), collaborative filtering (about 86%), content-based filtering (around 83%), and traditional search (approximately 65%).

F1-Score

The F1-score represents the harmonic mean of precision and recall.



The hybrid model achieves the highest F1-score (approximately 91–92%), outperforming deep learning

(around 88%), collaborative filtering (about 86%), content-based filtering (around 83%), and traditional search (approximately 65–67%).

V. DISCUSSION

The results demonstrate that the hybrid NLP-based recommendation system significantly improves personalisation and recommendation accuracy, achieving an overall performance of approximately 92%. By combining TF-IDF, cosine similarity, and collaborative filtering, the model effectively balances relevance and diversity while maintaining low computational complexity.

Compared to the traditional and deep learning approaches, the proposed system offers competitive performance with better scalability and interpretability. However, certain limitations remain, including a moderately sized dataset, a lack of real-time data integration, and partial resolution of the cold start problem.

Overall, the findings suggest that lightweight hybrid recommendation systems are practical and efficient solutions for e-learning platforms, supporting scalable, transparent, and resource-efficient implementations suitable for academic environments.

VI. CONCLUSION

This study presents a Hybrid NLP-based personalised e-learning recommendation system that improves course suggestion accuracy and relevance. By integrating content-based and collaborative filtering with TF-IDF and cosine similarity, the model achieved higher accuracy, precision, recall, and F1-score than traditional methods. It effectively reduces information overload and addresses overspecialization and cold start issues. The system remains computationally efficient, interpretable, and scalable, making it suitable for academic use. Compared to deep learning approaches, it offers a lightweight and

practical alternative. Overall, the framework enhances learner engagement and supports structured, data-driven academic decision-making in digital education environments.

VII. FUTURE WORK

Future research can enhance the hybrid NLP-based recommendation system by incorporating real-time behavioural data such as clickstreams, course completion, and user engagement to enable adaptive recommendations. Advanced techniques like neural collaborative filtering, transformers, and graph neural networks may improve accuracy, but must balance efficiency. Addressing the cold start problem through clustering and contextual modelling is essential. Large-scale, multi-institutional validation and cloud-based deployment can improve scalability. Additionally, explainable recommendations can increase user trust, while reinforcement learning can optimise long-term personalisation. Real-world testing through user studies and A/B testing will further validate system effectiveness and practical applicability.

VIII. REFERENCES

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