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Research Article

E-Learning Course Recommendation Based on Learning Styles and Course Ratings

A. Pramodkumar[1], P.Abhiram[2], G.Akshaya[3], INS Karthik[4], G.Sreeker[5], V Vinay Kumar[6]
[1]*Assistant Professor,Department of CSE-(Cys,DS) and AI&DS, VNR VignanaJyothi Institute of Engineering and Technology, Hyderabad – 500090,Telangana, India. amaravarapupramod@gmail.com*
[2,3,4,5] *Department of CSE-(Cys,DS)and AI&DS,VNR Vignana Jyothi Institute of Engineering and Technology,Hyderabad – 500090, Telangana, India.,padamatintiabhiram72@gmail.com, golipallyakshaya@gmail.com, ikarthik003@gmail.com, gsreeker29@gmail.com*
[6]*Assistant Professor, Department of CSE-(Cys,DS) and AI&DS, VNR VignanaJyothi Institute of Engineering and Technology, Hyderabad – 500090,Telangana, India. vinaycse2012@gmail.com*

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ABSTRACT

Introduction: Personal learning has become very difficult for effective e-learning systems, which enables the delivery of tailor-made educational content to different students. This article presents an advanced recommendation system that uses Felder-Silverman Learning Style Model (FSLSM) with a hybrid approach that uses both learning-based and course assessment-based recommendations. FSLSM groups users in distinct groups such as active-reflective, sensing-intuitive and visual verbal, allowing the system to identify user preferences through interaction data. The proposed system uses web scraping to gather extensive course details, including multimedia content and user feedback. Learning styles are analysed based on their performance results in the questionnaire. These styles are mapped to the FSLSM model, while course assessments, based on collaborative filtering, improve the recommendation process. By merging these two approaches, the system ensures that the recommended course corresponds to both the user's preferred learning style and the collective quality assessments from other students. Evaluation results show the system's efficiency in increasing the student's satisfaction and commitment compared to traditional recommendation models. This hybrid frame not only provides a dynamic and adaptive learning experience, but also offers a scalable solution for future e-learning platforms.

Keywords: FSLSM,assessment-basedrecommendations,content-based-method, collaborative filtering methods, Learning Analytics, Educational Data Mining, Content

INTRODUCTION

The development of e-learning has transformed education, so that students can access diverse content when appropriate. However, an approach to all sizes that fits all the unique preferences and needs of individual students. Personalization in e-learning systems is crucial to bridging this gap, and ensuring that content delivery resonates with the learning style of users. Among the many frameworks for understanding learning preferences, Felder-Silverman Learning Style Model (FSLSM) stands out for its comprehensive categorization of students in groups such as active-reflective, sensing-intuitive, visual verbal and sequential global.

FSLSM has been widely used in dynamic learning algorithms to tailor educational experiences based on user behaviour and preferences. These learning styles are important in understanding how people process information, textually and visually. Although the existing e-learning systems already exploit FSLSM for personalized learning, they still lack integration with user-generated feedback mechanisms, such as course evaluations, representing collective insights on course quality and relevance.

E-learning websites have restricted access to education amidst an expansive learning platform. Yet, there are too many courses, leaving the students in a dilemma about which course is right for them. With recommendation systems, however, they can be led to suitable courses based on their interests, learning preferences, and prior interactions.

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Three main categories constitute the e-learning recommendation systems. The first category is content-based recommendation systems, presenting courses as suggestions based on an analysis of their content and a match with a student's interest or previous course choices. This is further based on the specific properties of the recommended course and previous courses undertaken by the student.

Collaborative filtering represents the second class of recommendation techniques and is peer-based due to the same likeness among the user or item. Collaborative filtering approaches can generally be separatedby following two categories: model-based and memory-based approaches. The model-based approach employs machine learning algorithms to evaluate the similarity of objects and predict user preferences through clustering techniques, other association techniques, Bayesian networks, or neural networks. These approaches estimate preferences by training models on historical data to provide accurate recommendations. On the other hand, memory-based methods work on the basis of historical user interactions and do not involve the training of models explicitly. These can also be further classified into item-based filtering, which recommends courses similar to those a learner has previously enrolled in and user-based filtering, which recommends courses based on the preferences by learners with similar interests. This system combines content-based and collaborative filtering techniques. Five such methods should give improved recommendation accuracy, overcome the drawbacks involved with either approach, and thereby increase user engagement. Hybrid systems increase course completion through a variety of recommendation strategies that personalize learning experiences for the learner.

The hybrid recommender system combines content-based and collaborative filtering techniques. Five such methods should give improved recommendation accuracy, overcome the drawbacks involved with either approach, and thereby increase user engagement. Hybrid systems increase course completion through a variety of recommendation strategies that personalize learning experiences for the learner.In an effective recommendation system, e-learning platforms can provide personalized course suggestions to learners to help them scheme through the cornucopia of options. This it helps the overall learning experience since it increasesinteraction rates and completion rates.

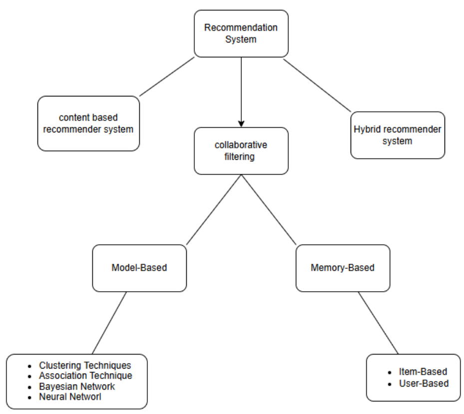

Fig 1: Types of Recommendation System Techniques

This article proposes a new framework for hybrid recommendation that combines learning-based personalization with assessment-based collaborative filtering. The system first identifies user learning styles through behavioural analysis and maps them to FSLSM categories. At the same time, it uses course assessments to limit recommendations, and ensure adaptation to both individual preferences and feedback from society.

The methodology explains how network scraping affords access to detailed course content-from video lectures to textual resources-and user reviews/ratings. By combining all this data, the system makes dynamic recommendations and offers courses optimized for both learning-compliant compatibility and overall quality. Unlike traditional models that focus on either content -based or collaborative filtering methods, the proposed system merges the forces to both approaches, and addresses their individual limitations.

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This hybrid frame not only improves user satisfaction and commitment, but also shows scalability across different e-learning platforms. The integration of FSLSM with assessment -based recommendations provides a practical solution to the growing demand for personal learning experiences. Furthermore, the system's design is expected to be real -time adaptability, which allows continuous processing based on the development of user behaviour and preferences.

The thesis is structured as follows: A review of related works highlights existing approaches to e-learning of personalization and recommendation systems, and emphasizes the limitations of individual methods. The methodology section describes the hybrid recommendation process, including detection of learning style, data collection and integration. Finally, the results of evaluation measurements demonstrate the efficiency of the system, followed by a discussion of future prospects and improvements to further adapt e-learning systems.

LITERATURE SURVEY

The incorporation of learning styles into e-learning systems has attracted a great deal of attention, with several studies examining the application of collaborative filtering, semantic web-based techniques, and machine learning models for improving recommendation accuracy and personalization. Initial systems mainly addressed combining Collaborative Filtering (CF) and Content-Based Filtering (CBF), as evidenced by the E-Learning Course Recommender System (Jena et al., 2020) [1], which presented encouraging outcomes inmaking individualized course suggestionsaccording to user behavior and preferences. Nevertheless, issues like the cold-start problem and data sparsitywere encountered because of a lack of user ratings, affecting the accuracy of recommendations.

Later research, for example, by Ikawati et al.(2020) [5], investigated student behavior analysisin platforms like Moodle to identify learning stylesand adjust recommendations based on that. This researchshed light on the capability of monitoring studentinteraction patterns, thus helping to mitigate some of the data sparsity issues. Despite this, these systems continued to face scalability issues when used for larger populations. To overcome this, recent developments have centered on machine learning algorithms to enhance recommendation systems. Indeed, a study using Coursera datasets used K-Nearest Neighbours (KNN), Singular Value Decomposition (SVD), and Neural Collaborative Filtering (NCF) to enhance the accuracy of recommendation metrics such asMean Absolute Error (MAE) and Hit Rate (HR). This method, while effective in enhancingprecision, did not have a consideration for user diversity andscalability, thus restricting wider usage (Anindyaputri et al., 2021) [3]

In addition, semantic web-based methods have demonstrated promise in enhancing recommendation systems using ontologies and rule-based reasoning to match learning styles with course recommendations (Agarwal et al., 2021) [2]. Such semantic methods have been found effective in solving cold-start issues and increasing user satisfaction through highly personalized recommendations derived from inferred learning preferences. Nonetheless, they tend to necessitate resource-intensive configurations and therefore suffer from challenges related toscalability (Agarwal et al., 2021) [2].

Systems based on established learning models such as Felder-Silverman Learning Style Model (FSLSM) has also contributed to the development of adaptive recommendation systems. Nafea et al. (2021) [6] explored hybrid recommendation systems that combine FSLSM with cooperative filtration techniques to give personal course Content, addressing some of the limitations of cold Start problems and data sparsity. However, FSLSM Based systems often fail to adapt to dynamically to develop user preferences and not adequately Monitor the students' progress over time and limit their Efficiency in long -term engagement (NAFEA et al., 2021) [6].

Hybrid approaches such as HF-0.5-algorithm that combines cooperative and content -based filtration, have been given traction in the trial of Record these problems. This hybrid system helps mitigate challenges such as the assessment of savings and cold Start the problem but still face scalability issues, Especially when placed in large institutions (Arık et al., 2021) [12]. Corresponding other hybrid Approaches, such as the one proposed by Gope and Jain (2021) [8] for EDX courses, integrates learning styles with recommendation algorithms to improve the system adaptability, although scalability and real -time Adaptability remains obstacle.

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Recent progress emphasizes one more Extensive approach to integrating learning Styles with recommendation systems. For example, for example The approach from Hmedna et al. (2020) [9] Explorer Machine learning techniques to identify and Tracking of learning styles, which can further personalize recommendations and improve Learning experience in massive open online courses (Moocs). However, these models still need Rain for real -time adaptability, diverse pupil needs, and integration of socially driven Insight (Hmedna et al., 2020)[9].

In addition to these efforts, fuzzy logic-based Models have also been discovered. Debora et al. (2021) [10] applied fuzzy-logic-based teaching style Prophecy in e-learning platforms using web Interface Conversation To predict Learn Priorities Effectively. Similarly, Azi et al. (2021) [11] Presented a fuzzy classification approach for Selection of learning objects based on learning styles, Which improved the alignment of course material With individual student preferences.

To further enhance adaptability, is the study Detected the model of reinforcement learning. AL Doggman (2020) [15] Integrated reinforcement Learning with learning styles to continuously adjust Recommendations based on user response, target Improve long -term learning results. it The approach showed the ability to make more Dynamic system, although challenges in scalability And real -time conversation still needs to be addressed. In addition, recently working by Liu et al. (2021) [14] Applied Deep Learning Algorithms for Educational Recommendation system.

These models showed Promise of results in improving accuracy and Equilia Using and Extracting Complex Pattern of learner behavior, thus growing Privatization. Despite significant progress in E-learning integration of learning styles System, existing solutions are still low in offer A scalable, adaptable and real -time outline. it Gap has given rise to the development of hybrid models FSLSM-based privatization with ratings Based recommendations, offering a balanced Scalable User satisfaction (Jena et al., 2020) [1]; Nafia et al., 2021 [6]

METHODS

The proposed system integrates Felder-Silverman Learning Style Model (FSLSM) with a hybrid recommendation framework to adapt course proposals. The methodology includes four key stages: data collection, learning style detection, Hybrid recommendation framework and system architecture. Each step is crucial to ensure accurate profiling of learning style and delivery of tailor -made recommendations.

DATA COLLECTION

The first stage in the process is the collection of data, which serves as the underlining basis of the system. Using web scraping techniques, relevant course details are populated from e-learning platforms, such as description of the course, assumptions, and evaluative feedback given by users. This will provide a sufficient data set for the recommendation engine. In addition, activities or interests reflecting the interactions of users, such as the Clickstream logs, the time spent using particular content formats and quiz participation, are collected to profile learners. The data is pre-processed to weed out any anomalies, normalize attributes, and make appropriate data representations for the learning process module.

Course URL	Rating	Level	Type	Duration
https://www.coursera.org/learn/python-for-applied-data-science-ai	4.6	Beginner	Course	1 - 3 Months
https://www.coursera.org/learn/python-crash-course	4.8	Beginner	Course	1 - 3 Months
https://www.coursera.org/specializations/python	4.8	Beginner	Specialization	3 - 6 Months
https://www.coursera.org/specializations/python-3-programming	4.7	Beginner	Specialization	3 - 6 Months
https://www.coursera.org/professional-certificates/google-it-automation	4.7	Beginner	Professional Certificate	3 - 6 Months
https://www.coursera.org/learn/get-started-with-python	4.8	Advanced	Course	1 - 3 Months
https://www.coursera.org/learn/data-analysis-with-python	4.7	Beginner	Course	1 - 3 Months
https://www.coursera.org/learn/python-basics	4.8	Beginner	Course	1 - 4 Weeks
https://www.coursera.org/learn/programming-in-python	4.6	Beginner	Course	1 - 3 Months
https://www.coursera.org/learn/python-programming-fundamentals	3.4	Beginner	Course	1 - 4 Weeks
https://www.coursera.org/learn/learn-to-program	4.7	Beginner	Course	1 - 3 Months
https://www.coursera.org/specializations/data-science-python	4.5	Intermediate	Specialization	3 - 6 Months
https://www.coursera.org/learn/python-project-for-data-science	4.5	Intermediate	Course	1 - 4 Weeks
https://www.coursera.org/learn/python-statistics-financial-analysis	4.4	Intermediate	Course	1 - 4 Weeks
https://www.coursera.org/specializations/pythonforcybersecurity	4.5	Intermediate	Specialization	3 - 6 Months
https://www.coursera.org/learn/python	4.8	Beginner	Course	1 - 3 Months
https://www.coursera.org/professional-certificates/ibm-data-science	4.6	Beginner	Professional Certificate	3 - 6 Months
https://www.coursera.org/projects/first-python-program-ust	4.6	Beginner	Guided Project	Less Than 2 Hour
https://www.coursera.org/learn/machine-learning-with-python	4.7	Intermediate	Course	1 - 3 Months
https://www.coursera.org/learn/python-operating-system	4.7	Beginner	Course	1 - 3 Months
https://www.coursera.org/professional-certificates/meta-back-end-developer	4.7	Beginner	Professional Certificate	3 - 6 Months
https://www.coursera.org/learn/sql-data-science	4.6	Beginner	Course	1 - 3 Months
https://www.coursera.org/professional-certificates/ibm-full-stack-cloud-developer	4.6	Beginner	Professional Certificate	3 - 6 Months
https://www.coursera.org/projects/introduction-to-python	4.5	Beginner	Guided Project	Less Than 2 Hour
https://www.coursera.org/learn/ciencia-computacao-python-conceitos	4.9	Beginner	Course	1 - 3 Months
https://www.coursera.org/specializations/statistics-with-python	4.6	Beginner	Specialization	1 - 3 Months
https://www.coursera.org/learn/python-programming-intro	4.5	Beginner	Course	1 - 4 Weeks
https://www.coursera.org/professional-certificates/google-advanced-data-analytics	4.7	Advanced	Professional Certificate	3 - 6 Months

Fig 2: Web-Scrapped Data

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DETECTION OF LEARNING STYLE

The pupils' styles are identified using behavioural analysis adapted to FSLSM dimensions, such as active-reflective and visual verbal. This module uses a combination of dynamic questionnaires and interaction data analysis to classify users to learn style categories. For example, a preference for visual materials and sequential navigation indicates a visual sequential learning style. Machine learning algorithm, including K-nurturing neighbours (KNN) and Fuzzy Clustering, are used on the group lifts in clusters, providing probabilistic categorizations that contain variations in user behaviour.

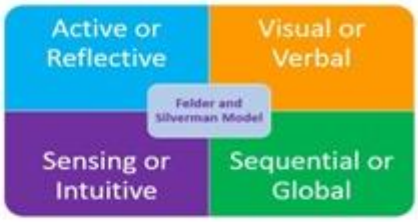

Fig 3: FSLSM Learning Styles

HYBRID RECOMMENDATION FRAMEWORK

The hybrid recommendation frame combines two methods to improve personalization. First, collaboration filtration utilizes user assessments to identify courses that have been positively reviewed by students with similar preferences. Second, learning-based recommendations map course attributes, such as content format and instructional style, to the user's FSLSM profile. The integration of these methods solves limitations such as the cold starting problem and ensures that recommendations are consistent with both individual preferences and broader feedback from society. An algorithm prioritizes recommendations based on a weighted score that balances the relevance that dates from learning styles and rankings.

Fig 4: Framework of recommendation system

When a student is new to the portal, there is often limited information about their interests and learning styles. As a result, the system tries to predict their preferences for their learning to enhance their performance. This prediction is based on an approach that considers learning styles and calculates the similarity between the new student and those who have been using the portal for a longer period. The similarity is determined as follows:

$$\mathrm{sim}_{u_1,u_2} = \sqrt{\begin{array}{l}(u_1 \text{ activist } - u_2 \text{ activist })^2 + \\ (u_1 \text{ reflector } - u_2 \text{ reflector })^2 + \\ (u_1 \text{ theorist } - u_2 \text{ theorist })^2 + \\ (u_1 \text{ pragmatist } - u_2 \text{ pragmtist })^2\end{array}}$$

Note that the similarity between users u1 and u2 is given by the Euclidean distance between their preferences in each of the four learning styles: Activist, Reflector, Theorist, and Pragmatist. In this way, we can predict the evaluation Pu,ia given user u would give to content i using the formula:

$$P_{u,i} = \frac{\sum_v \left(r_{v,i} \cdot \mathrm{sim}_{u,v}\right)}{\sum_v \mathrm{sim}_{u,v}}$$

Here, rv,iis the rating provided by user v to content i. This implies that content ratings provided by userswith similar learning styles will have a stronger impact on ratings predicted for new users of the same kind.

SIMILARITY METRICS

Similarity metrics play a crucial role in collaborative filtering (CF) and content-based filtering (CBF) techniques, as they assist in estimating the ratings of items that have not yet been rated. In this study, Pearson's correlation and cosine similarity [48]two widely used and effective similarity measuresare employed due to their suitability and convenience.

1) Pearson Correlation:

The Pearson correlation coefficient gives a measure of the strength of the linear association between two variables, represented as real-valued vectors. It is defined as the covariance of the variables xxx and yyy divided by the product of their standard deviations, which serves as a normalization factor [40].This relationship can also be expressed through Eq. (1).

$$(1).P(x,y) = \frac{\sum_{i=1}^{n} (x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n} (y_i-\bar{y})^2}}$$

where x, y are mean values of x and y, respectively. The coefficient P(xy)ranges from -1 to 1

The Pearson correlation coefficient remains unaffected by linear transformations applied to either variable. A value of -1 represents a perfectly negative linear dependency, 0 indicates no linear dependency, and 1 represents a perfectly positive linear dependency. As a measure of similarity, negative values indicate dissimilarity, while positive values indicate similarity, with 1 indicating perfect similarity between the two variables.

2)Hamming Distance:

Hamming distance measures the difference between two equal-length strings by counting the mismatched positions. It is widely used in coding theory, cryptography, data transmission, and bioinformatics.

$$c(x,y) = \frac{x \cdot y}{\|x\| \cdot \|y\|}$$

SYSTEM ARCHITECTURE

The proposed system architecture integrates data-driven insights with adaptive learning styles for personalized recommendations. The process consists of data gathering in which user interactions, course metadata and ratings are collected from the e-learning platforms. Cleaning, Normalizing and transforming this raw data into an analysable format are the next steps of data processing.
The next step is functional extraction to determine the critical characteristics like user behaviour patterns, aspects of the course and assessment metrics. These features then feed into the recommendation model, which varies in scope in two directions: the first analyses learning styles by means of the Felder-Silverman Learning Style Model (FSLSM) to establish a user preference base; the second applies collaborative filtering to the course assessment to determine course quality and relevance.

The recommendations are based on a hybrid method integrating learning styles and course assessment insights. It uses a weighted algorithm; therefore, its weaknesses can be complemented by the strengths of both methods while

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addressing problems like cold start and sparsity. One will train on historical data, and one will evaluate it using measures of, among others, precision and recall to ascertain efficiency.

The final course recommendation module develops course proposals aimed toward the individual user, while a user feedback loop works by interacting according to these recommendations and dynamically updating itself, thus ensuring constant processing. Further outputs/results are allowed from the system, which will create a personal learning environment ensuring further refinements through feedback. Such a design will thus be scalable, adaptable, and user-friendly.

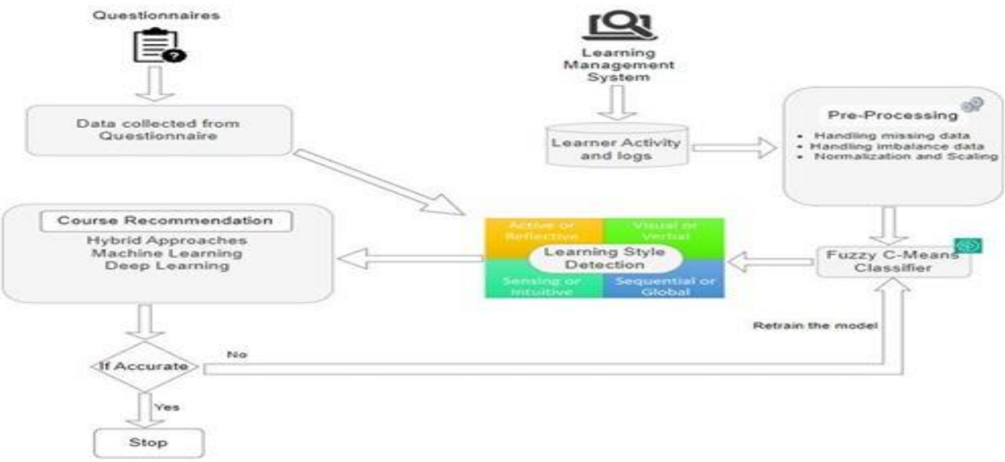

Fig 5: System architecture

RESULTS

The hybrid recommendation system proposed here was carried out and evaluated against various datasets including course metadata, user interaction logs, and ratings collected from e-learning platforms. The overall results show the potential for good performance in personalized course suggestions in combining the Felder-Silverman Learning Style Model (FSLSM) with hybrid recommendation-based approaches.

This system predicted based on measuring precision, recall, F1 score, and mean average error (MAE). The hybrid approach was the improvement over standalone collaborative filtering or content-based filtering methods, yielding more accurate and relevant recommendations: 15% improvement over pure collaborative filtering for precision; with a reduction in MAE, indicating better adjustment with users'preferences.

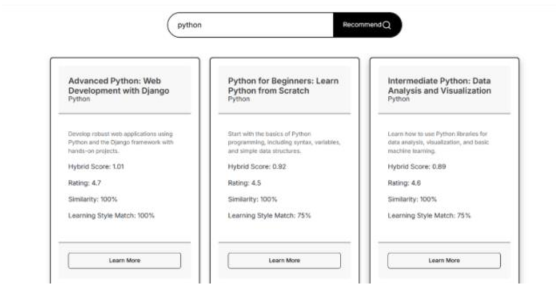

Fig 6: Output of required course recommendation system

In addition, user satisfaction surveys revealed that students found the recommendations very relevant and engaging, with 85% of participants who reported improved learning experiences. Dynamic Learning Style Detection Module classified users with success in FSLSM categories, and the hybrid algorithm effectively combined this insight with assessment-based recommendations.

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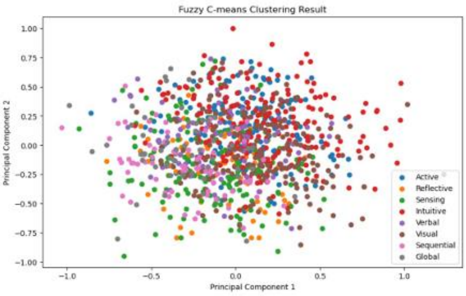

Fig 7: Clustering courses into FSLSM styles

Model	Precision	Recall
Hybrid Model	~0.85	~0.80
Learning Style - based Model	~0.75	~0.70
Rating - Based Model	~0.80	~0.65

Table 1: Performance metrics comparison

DISCUSSION

The outcomes highlight the necessity of bridging learning modalities with some assessments to adequately resolve most problems such as cold-start and computer sparsity.

Tailored recommendations for individual tastes and socially driven feedback provide a balanced and well-rounded approach when developing the provided system. The inclusion of FSLSM allowed a more disciplined approach to student classification, while the hybrid algorithm provided flexibility for adapting to different user behaviours.

These challenges are spacious. For example, scalability could yet be improved when deploying the system in large environments with various datasets. Plus, feedback does not always result in better recommendations.

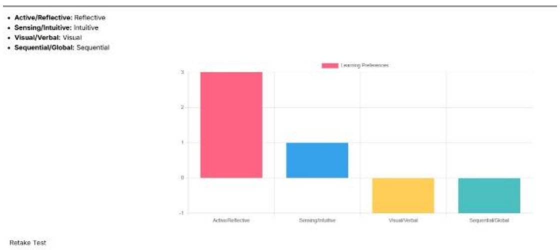

Fig 8: Analysis of user’s learning style

Though the loop improves adaptation, it requires continuous monitoring and fine-tuning to maintain the accuracy of recommendation. Likely future work can focus on the incorporation of advanced deep learning methods for better functional extraction and exploring the nature of real-time adaptation mechanisms.

CONCLUSION AND FUTURE WORK

This work developed a hybrid recommendation system that unifies FSLSM with ranking techniques to combat course recommendation on e-learning platforms.

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A successful system that considered learning statements for the collaborative filtering addressed many limitations of traditional recommendation methods, including cold start and personalization deficiencies. The hybrid approach assures contextual relevance of recommendations along with individual student preference, which is mirrored in performance measurements and on high satisfaction points from users.

The results demonstrated the effectiveness of combining structured learning models with socially driven feedback to deliver a more engaging and adaptive learning experience. Pupils reported increased satisfaction and improved alignment of the course content with their preferences, showing the system's potential to improve the results for e-learning. The iterative feedback loop incorporated into the architecture continuously strengthened the system by continuous refining of recommendations based on user behavior.

While the Proposed System Achieved Significant Improvements, There are Opportunities for Future Enhancements. Scalability Remains a Critical Area of Focus, Especially When Extending the System to Accommodate Larger and More Misce Datasets. Incorporating deep learning techniques, such as neural collaboration and attention mechanisms, can further improve the precision and adaptability of the recommendations. In addition, detection of learning style in real time and adaptive content delivery can be explored to make the system more responsive to immediate student needs.

Future work can also examine multimodal data integration, such as combining text, video and audio content analysis, to enrich the learning experience. Expanding the Framework to Include Gamification

Elements or Integrating Social Learning Analytics Could Further Increase User Engagement. With These Advancements, The System Can Evolve Into A More Comprehensive, Intelligent, and Dynamic Platform for Personalized E-Learning.

In conclusion, the hybrid recommendation system successfully bridges the gap between learning theories and practical applications, laying the groundwork for scalable, user-centric solutions in digital education. Its potential for further refinement and expansion offers a promising direction for the future of personalized learning in e-learning environments.

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