Sr. No	Paper	Year	Methodology	Performance metrics	Limitations
1.	Recommendation System for Elective Courses using Content-based Filtering and Weighted Cosine Similarity	2021	Recommendations are made by calculating weighted cosine similarity between curriculum and student profiles, yielding a list of elective course suggestions.	From the system testing, the average results of non-weighted recommendation testing for the relevance attribute were 68%, the novelty was 90.67%, serendipity was 72.67%, and increasing recommendation diversity was 80%. Then for the average results of weighted recommendation testing for the relevance attribute of 78.67%, the novelty of 90.67%, the serendipity of 75.33%, and increasing recommendation diversity of 80%.	**Limited Recommendation Diversity**: The content-based filtering approach might lead to limited diversity in recommendations since it primarily relies on the characteristics of the user's past courses. This could result in overlooking potentially interesting courses that are outside the scope of the user's previous selections.
2.	Improved course recommendation algorithm based on collaborative filtering	2020	The process involves: collecting data on student course preferences, constructing a user-item interaction matrix representing preferences	Precision, recall, and F1-score can be used to measure how well the algorithm's recommendations	**Cold Start Problem**: The collaborative filtering approach might struggle with providing accurate

			or enrolments, preprocessing data to handle missing values and normalize, calculating similarity between users or items, predicting missing ratings based on similar ratings, generating top-N course recommendations, and evaluating the algorithm's performance using metrics like accuracy, precision, recall, F1-score, or mean squared error.	match actual user preferences.	recommendations for new users or courses with limited interaction data.
3.	Course Recommendation System: Collaborative Filtering, Machine Learning and Topic Modelling	2022	The process includes: collecting data on student course preferences and attributes, applying collaborative filtering to predict preferences using an interaction matrix, extracting features from course descriptions, employing machine learning to combine features and collaborative filtering, using topic modeling to identify themes in course descriptions, enhancing recommendations with extracted topics, and evaluating system	Evaluation metrics include accuracy measures like MAE and RMSE for predicted preferences, top-N recommendation metrics such as precision, recall, and F1-score, along with diversity metrics. For topic modelling, coherence scores evaluate topic interpretability. System coverage is assessed by the portion of recommended	**Data Quality**: The effectiveness of the recommendation system heavily relies on the quality and completeness of the input data. Inaccurate or incomplete data could lead to suboptimal recommendations.

			performance using diverse metrics.	courses. Novelty is checked to ensure diverse suggestions. User satisfaction is potentially measured through feedback and surveys.	
4.	A Collaborative Recommendations for Online Course Recommendations	2019	The process involves: collecting user interactions with online courses, forming a user-item interaction matrix, preprocessing data by addressing missing values and normalization, calculating similarity between users or courses, predicting missing ratings or interactions using similar user behaviours, generating top-N course recommendations for each user, and evaluating system performance using diverse evaluation metrics.	The evaluation includes accuracy metrics like MAE and RMSE for predicted interactions, top-N recommendation metrics such as precision, recall, F1-score, or CTR, measuring system coverage in percentage of the course catalogue, evaluating the novelty of recommended courses for diversity, assessing diversity for varied user choices, measuring serendipity for engaging unexpected recommendations, and gauging user satisfaction through feedback or surveys.	**Data Sparsity**: Collaborative filtering can be less effective if the interaction data is sparse, leading to inaccuracies in interaction predictions.

5.	A Matrix Factorization-based Collaborative Filtering Framework for Course Recommendations in Higher Education	2023	The process includes: collecting student course data, constructing a user-item interaction matrix showing preferences, using matrix factorization to find latent factors capturing patterns, extracting features, predicting ratings based on these factors, generating top-N course recommendations, and evaluating system performance using diverse metrics.	The evaluation entails: accuracy metrics like MAE and RMSE for predicted interactions, top-N recommendation metrics such as precision, recall, F1-score, measuring system coverage in the course catalogue percentage, assessing novelty of recommendations for diversity, measuring recommendation diversity for varied options, and potentially using user feedback or surveys to gauge user satisfaction and relevance.	**Scalability**: As the volume of users and courses grows, the computational demands of matrix factorization can increase, potentially affecting real-time recommendation capabilities