International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(5s) 2026 pp. 873-888
https://doi.org/10.70917/ijcisim-2026-2810
Article

An Adaptive AI Framework for Student Domain and Career Guidance

Neha Bhaidasna[1], Sandeep Vasant[2], Jaideep Raulji[3]

[1] M.K.Institute of computer studies, Bharuch, Research scholar, Navrachana University, Vadodara, Gujarat India. neha.bhaidasna@nuv.ac.in

[2] Department of Computer Science and Engineering, Navrachana University, Vadodara, Gujarat, India

[3] Department of Computer Science and Engineering, Navrachana University, Vadodara, Gujarat, India

Abstract: Choosing an appropriate academic stream and career path is a complex decision for students due to the wide range of educational and professional opportunities available today. This paper proposes an Adaptive AI Framework for Student Domain and Career Guidance that supports personalized academic and career recommendations based on students' interests, aptitude, preferences, and cognitive abilities. The framework operates through three stages: student profiling and assessment, academic stream classification, and domain-specific recommendation generation. A structured questionnaire and weighted scoring mechanism are used to evaluate student responses and identify suitable academic domains. In addition, a domain-specific keyword repository is incorporated to improve recommendation relevance. The framework also outlines the future integration of Small Language Models (SLMs), Large Language Models (LLMs), and Retrieval-Augmented Generation (RAG) to enable adaptive questioning and more personalized assessments. The proposed approach provides an intelligent and scalable decision-support system that can assist students and career counselors in making informed academic and professional choices.

Keywords: Filtering Techniques, Career guidance, Domain recommendation, Adaptive Assessment, Language model, RAG (Retrieval-Augmented Generation), Fine-Tuning, SLM/LLM

1. Introduction

Selecting an appropriate academic domain and career path is one of the most critical decisions in a student's educational journey. An improper choice may lead to reduced academic performance, dissatisfaction between individual capabilities and professional opportunities. Traditional counseling methodologies primarily depend on on expert guidance, aptitude assessments, and fixed questionnaires. While these methods provide useful insights, they often lack personalization and scalability when applied to large student populations.

Recent advances in Artificial Intelligence (AI) and recommendation systems have enabled the development of intelligent decision-support tools capable of providing personalized suggestions [1]. Recommendation techniques such as Collaborative Filtering, Content-Based Filtering, and Hybrid Models have demonstrated significant success in domains including e-commerce, entertainment, and online education. However, their application to academic domain selection remains limited due to challenges associated with student profiling, adaptive assessment, and explainable recommendations.

To address these challenges, this paper proposes an Adaptive AI Framework for Student Domain and Career Guidance. The framework combines structured assessment techniques, recommendation methodologies, and language-model-based interaction mechanisms to evaluate students' interests, cognitive abilities, and academic preferences. Unlike conventional systems that rely on static questionnaires, the proposed framework supports adaptive domain-specific assessment and personalized recommendation generation.

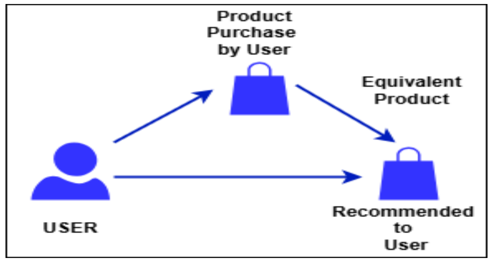

Fig. 1 Book Recommendation System

The proposed framework consists of three major phases: (i) student profiling and data pre-processing, (ii) academic stream classification, and (iii) domain-specific evaluation and recommendation. The objective is to assist students in identifying academic domains that align with their interests, aptitude, and long-term career aspirations while providing a scalable decision-support mechanism for academic counselors.

1.1 Recommendation System Lifecycle

Recommendation systems are developed through a series of stages, including data collection, storage, preprocessing, analysis, model evaluation, deployment, and continuous learning. These stages enable the system to identify user preferences, generate personalized recommendations, and improve performance over time through regular updates and feedback.

1.2 Recommendation System Algorithms

Recommendation systems often use matrix-based methods, clustering, and deep learning [4]. The Clustering approach groups users or items with similar features but may lack strong personalization (see Figure 2). In Deep learning, it analyzes complex user behavior for more accurate and tailored suggestions.

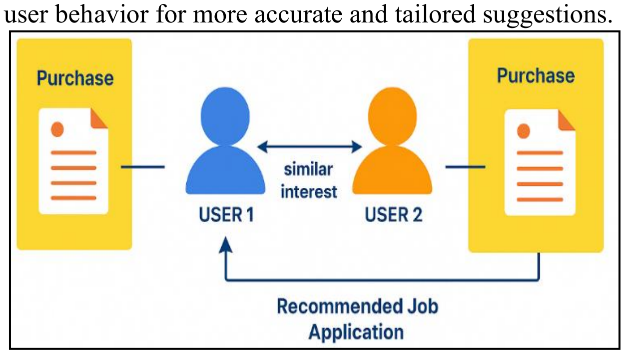

Fig. 2 Product recommend system for users having similar interest

1.3 Overview of Recommendation Systems

Recommendation systems generally employ three major approaches: Collaborative Filtering, Content-Based Filtering, and Hybrid Recommendation Techniques [5].

Collaborative Filtering generates recommendations by identifying similarities among users or items based on their interaction history. It can be implemented through user-based or item-based strategies and is based on behavioral data rather than item characteristics [6]. Content-Based Filtering recommends items by analyzing their attributes and matching them with a user's previous preferences. Items with similar features to those previously liked by the user are prioritized for recommendation (see Figure 3). Hybrid Systems integrate both collaborative and content-based approaches to improve recommendation quality and overcome the limitations of individual methods. For instance, in movie recommendation platforms, user viewing patterns and search activities are combined with movie attributes to suggest relevant content (see Figure 4). This embedded approach helps address issues such as data sparsity and the cold-start problem while enhancing recommendation accuracy [7].

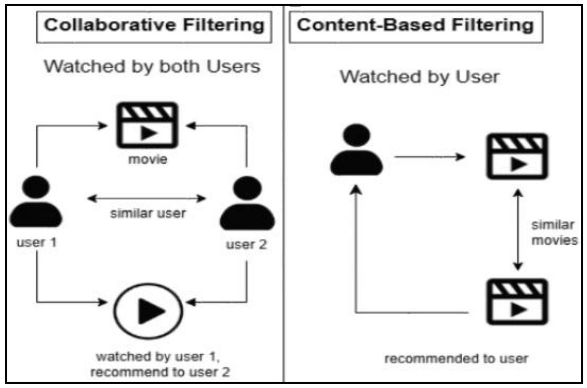

Fig. 3 Collaborative & Content-Based filtering

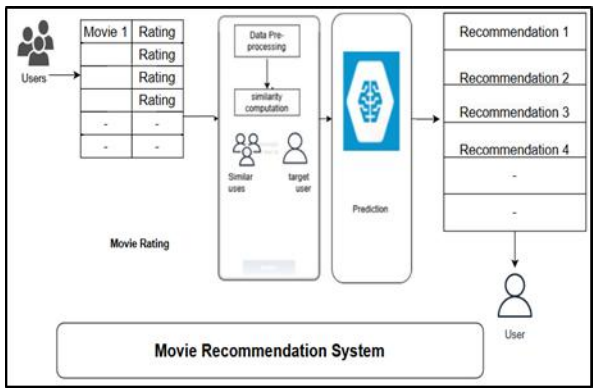

Fig. 4. Movie recommendation System

1.4 Applications Domain of Recommendation Systems

Recommendation systems are extensively used across various domains to deliver personalized content and services. E-commerce platforms identify suitable products based on user preferences, while streaming services deliver customized music, movies, and videos selection aligned with individual interests. Social media and search engines also utilize recommendation techniques to enhance user engagement and improve content discovery [8].

1.5 The Role of Recommendation Systems in Career Navigation

With the growing diversity of academic and career opportunities, students often face difficulties in approaching suitable paths that match their interests and abilities [9]. Such kind of recommendation framework and AI enabled systems enhance the decision making process by analysing student's interest, ability and profiles to deliver personalized academic and career guidance.

1.6 Various Recommendation Systems in Education

Many modern e-learning platforms leverage recommendation systems to deliver personalized learning experiences. By analyzing user interests, learning history, and performance, these systems suggest relevant courses, study materials, and skill-development opportunities. Such personalized guidance helps learners improve their knowledge, develop new competencies, and progress toward their academic and career goals.

1.7 Advantages of Recommendation Systems for Students

- Personalized Learning Paths: Tailored suggestions help students focus on their goals and address their unique learning needs.
- Time Efficiency: Directing students to the most relevant resources saves time and boosts productivity.
- Enhanced Engagement: Personalized content keeps students motivated by matching their interests and abilities.

• Proactive Support: Identifying areas of difficulty early enables timely interventions to address challenges.

• Goal Alignment: Recommendations aligned with long-term objectives ensure students stay on track to achieve their aspirations.

2. Related Work

The paper presents a ML-based job title classification system for online recruitment [10]. It utilizes Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) for hierarchical, multi-label taxonomy. Semi-supervised methods enhance scalability, while future improvements, like O*NET-SOC taxonomy adoption, offer promise. Experimental results demonstrate its potential to improve job search accuracy.

The study highlights in "Recommender Systems: An Overview of Different Approaches to Recommendations" reviews all major recommendation techniques [10]. It discusses their several benefits, also face some challenges such as scalability issues and over-specialization. Emphasizing hybrid models, it focuses their role in improving recommendation accuracy and evaluation through metrics like MAE and RMSE.

A hybrid recommendation framework combining content-based, collaborative, and knowledge-based filtering was developed by Chhikara and Malik. The approach utilized sentiment analysis of Zomato reviews to improve the relevance of restaurant recommendations. The model improves personalization by merging semantic social networks with machine learning and demonstrates the efficiency of collaborative filtering over time. [11].

Suhasini Parvatikar and Dr. Deepa Parasar analyze Recommendation Systems (RS) and their role in e-commerce [12]. The paper discusses how RS reduces information overload through personalized suggestions, categorizing approaches into personalized and Non-Personalized. It details five filtering techniques and highlights hybrid models' effectiveness, emphasizing similarity computations like Pearson Correlation and Cosine Similarity.

The proposed methodology in a paper focuses on "Movie Recommendation System" presents a hybrid approach to optimize recommendation accuracy [13]. Using algorithms like SVD and cosine similarity, it leverages metadata (cast, crew, genre) and distance metrics (Euclidean, Manhattan) to address diversity and sparsity. Results show improved precision, benefiting OTT platforms and overcoming traditional RS limitations.

This paper presents an advanced article recommendation system that personalizes suggestions for researchers based on their field and past publications [14]. Using datasets from ACM, IEEE Xplore, and DBLP, it analyzes metadata with TF-IDF and cosine similarity. Results showed 71% relevance, highlighting its effectiveness in enhancing research article discovery.

A "Product Recommendation System: A Comprehensive Review" examines multiple filtering strategies, examining the algorithms like K-Nearest Neighbor and matrix factorization for predicting user preferences [15]. Featuring examples from Amazon and Netflix, it emphasizes recommendation systems' impact on customer experience and sales, though deeper experimental validation could enhance its insights.

The framework in "Recommendation Systems in Education: A Systematic Mapping Study" reviews 44 studies on educational recommendation systems, focusing on academic choices, e-learning, and personalized learning [16]. The approach combine several recommendation mechanism to deliver personalized result emphasizing web-based platforms. The study identifies gaps in AI-driven personalization and accuracy, underscoring the transformative potential of recommendation systems in education.

The study focuses in paper presents a course recommendation system for e-learning platforms, leveraging machine learning techniques like clustering, classification, and collaborative filtering to personalize suggestions [17]. Using TF-IDF, Count Vectorizer, and cosine similarity, it achieves 96% accuracy with logistic regression. While effective in fields like Business Finance, it notes limitations in dataset scope and student preference data.

Kumari and Patil introduced a multi-level recommendation system for personalized tourism using sentiment analysis and collaborative filtering. Their framework effectively extracts user sentiments from reviews to rank destinations, improving recommendation relevance. The study highlights how integrating sentiment-based analysis with traditional filtering enhances user satisfaction in tourism-related services, contributing valuable insights to hybrid recommender system design [18].

SKYNET, developed by Aakash Kolekar, is a professional networking platform that uses machine learning for job recommendations [19]. It applies TF-IDF and Naive Bayes classification to match candidates based on certifications, experience, and academics. Integrating content-based, collaborative, and hybrid filtering, SKYNET addresses standardization and privacy while offering secure, user-friendly job alerts and candidate rankings.

Artificial Intelligence-based Design (AID) enhances career matching for university students using Mixed Integer Linear Programming (MILP) and cluster analysis [20]. Surpassing traditional methods like the Hungarian Method, AID employs multi-objective optimization and Genetic Algorithms, achieving a 91% match rate for 84 students and 54 companies. The study emphasizes AID's potential to revolutionize career placements.

The noval approach proposed by M. Rekha Sundari, G. Shreya, and T. Jawahar improves elective course selection in a choice-based credit system [21]. It uses a knowledge-based classification method to align student interests through aptitude, categorizing courses into Programming, Logical, Conceptual, and Theoretical. By exploring academic history, it improves the selection accuracy, though scalability challenges suggest potential improvements with dynamic algorithms.

The work bring together a Skills and Occupation Knowledge Graph (KG) enriched with job posting data to boost job-candidate matching [22]. It integrates ISCO and ESCO taxonomies, using methods like link prediction, Node2Vec, and TF-IDF for skill relevance. Applications include skill gap analysis and career transitions. Despite its potential, the study notes limitations in validation and dataset reliance.

The paper introduces a self-learning job-matching system that enhances accuracy using ontology-based inference and a Standard Template for resume consistency [23]. It parses content contextually, auto-fills missing data, and ranks resumes with approximate string matching. While promising, real-world validation is needed. This framework addresses traditional system limitations, improving intelligent job matching.

The research point outs a hybrid Educational Recommendation System (ERS) integrating Student-Based, Teacher-Based, and Domain-Based recommenders for personalized learning [24]. A conversational engine enhances data collection, tackling sparsity issues. Evaluated on precision, recall, and unexpected recommendations, the system shows promise but faces challenges in real-world implementation and scalability. It offers a holistic approach to personalized learning.

The finding indicates in a paper a personality-oriented recommender system for cross-domain course selection, using Holland code traits and course performance data [25]. It operates in two phases: offline similarity calculation and online recommendation based on similar students. Tested on 710 students at Cheng Shiu University, it achieved 95.54% approval, enhancing personalized learning by aligning interests with career goals.

The paper reviews recommender systems (RS) for course selection, categorizing them into various filtering methods [26]. It highlights hybrid approaches' efficacy while addressing challenges like course abundance and limited guidance. Despite scalability issues, RS enhances decision-making and market alignment, offering transformative potential for modern education.

The study outlines a Personalized Course Recommender System (PCRS) integrates multiple recommendation techniques to provide personalized suggestions with ontology techniques [27]. It increase accuracy through N-gram query classification and WordNet-based expansion. Tested on 300 M.Tech courses, it achieved 95.25% accuracy. Despite practical challenges, PCRS shows strong potential for personalized e-learning recommendations.

The work discusses in a Course Enrollment Recommender System (CERS) that personalizes semester course planning using data mining [28]. It considers skills, interests, prerequisites, and difficulty levels. Tested at Masaryk University, S1 achieved the highest precision, while S2 had the most student satisfaction. Features like a Semester Selection algorithm and color-coded difficulty indicators enhance course selection and student experience.

The paper explores course selection techniques using data mining, including k-nearest neighbors and matrix factorization. Authors uses an automated elective course recommender by combining collaborative filtering and association rule mining [29]. It clusters students by grades with k-means and applies K-nearest neighbor to identify course-grade patterns. Tested on 2,000 Electrical Engineering students, it achieved 0.95 precision but faced recall trade-offs. While effective, its single dataset limits generalizability, requiring future improvements.

Biased matrix factorization performed best (RMSE 0.831) using Can Tho University data [30]. The system offers grading prediction, course recommendations, and advisor support. While effective, it requires refinements like prerequisite constraints, providing valuable insights for enhancing academic planning.

Table 1: Comparison and analysis of various techniques and algorithms for Recommendation Method

PAPER TITLE	DOMAIN	TECHNIQUE USED / ALGORITMS / Tools	DATASET	EVALUATION OR RESULT	CONCLUSION
10. Recommender Systems: An overview of different approaches to recommendations	E-commerce	Collaborative filtering, Content-based filtering, Hybrid methods	Not specific	Discusses issues like Best Item Problem, Top-N Problem, and compares traditional methods like CF, SVD, KNN, and Bayesian clustering	Recommender systems improve user experience by addressing challenges like data sparsity and cold start.
11. Recommendation System Using Machine Learning	E-commerce	Personalized (CF, Content-based, Demographic, Hybrid) and Non-Personalized methods	Amazon, Myntra	Combines multiple techniques like Naïve Bayes and KNN, improving prediction accuracy	Personalized recommendation systems enhance user experiences and increase sales by providing relevant suggestions.
12. Movie Recommendation System	Entertainme nt	Collaborative filtering (SVD), Cosine similarity	Not specific	Improves recommendation quality by uniting multiple techniques to address information overload and deliver more relevant suggestions.	Recommender system enhances recommendation accuracy by using collaborative and hybrid approaches for personalized suggestions.
13. A Paper Recommendation System Based on User's Research Interests	Academic Research	Cosine similarity, TF-IDF, metadata analysis	ACM, IEEE Xplore, DBLP	47% of emails opened, 29% of articles read, 71% of recommendati-ons marked as relevant	Personalized article recommendations based on prior research work save time and improve relevance for researchers.
14. Product Recommendation System a Comprehensive Review	E-commerce	Content-based filtering, Collaborative filtering, Hybrid methods	Not specific	Combines user-item interaction data and matrix factorization to improve recommendation precision	Hybrid systems enhance user satisfaction by providing diverse and accurate product suggestions, avoiding reliance on popular items.
15. Recommendation Systems in Education: A Systematic Mapping Study	Education	Hybrid, Collaborative filtering, Content-based filtering	Scopus, IEEE Xplore, ACM, Web of Science	44 primary studies; hybrid methods are most common in educational RS, covering various academic decisions, e-learning, and student deficiencies	RS improve personalization in education by recommending relevant materials, courses, and academic paths, addressing key challenges like accuracy.

PAPER TITLE	DOMAIN	TECHNIQUE USED / ALGORITMS / Tools	DATASET	EVALUATION OR RESULT	CONCLUSION
16. Course Recommendation System for E-Learning	Education	Collaborative filtering, Clustering, Logistic regression	Not specific	Achieved 96% accuracy in predicting relevant courses	Recommender systems simplify course selection by providing personalized recommendations, improving e-learning experiences.
17. SKYNET: Professional Networking Platform	Job Market	TF-IDF, Naïve Bayes, CSRF tokens	Not specific	Achieved 82% accuracy and 78% precision in predicting job suitability	Efficient job recommendation system bridges the gap between students and employers, enhancing career opportunities.
18. AID: Artificial Intelligence based Career Matching	Job Market	Mixed Integer Linear Programming, Cluster analysis, Genetic algorithms	Not specific	91% perfect match rate for career placement	AI-based systems optimize career matching, improving the accuracy of placements between students and companies.
19. Course Recommendation System	Education	Rule-based classification	Not specific	Improved academic outcomes with higher grades for students using the system compared to those selecting courses independently	Rule-based CRS matches students' interests and capabilities, improving accuracy and recommendation quality in elective selection.
20. Job Posting-Enriched Knowledge Graph for Skills-based Matching	Job Market	Knowledge Graph, TF-IDF, N-gram model, Jaccard distance	60,000 Dutch job vacancies	Dynamic KG integrates real-time job postings for skill matching	Knowledge graph approach holds potential for improving labor market efficiency and skill-based job matching.
21. Intelligent Job Matching with Self-Learning Recommendation Engine	Job Matching	Ontology, Self-Learning Engine, Approximate String Matching	HR data from Malaysia	Effectively identifies best candidates using a distance calculation method. Limited real-world evaluation and generalizability	Shows promise in enhancing job matching, but needs real-world implementation and adaptability across industries
22. What to Learn Next: Incorporating Student, Teacher, and Domain Preferences for a Comparative Educational Recommender System	Educational Recommendation	Hybrid approach: Student-Based, Teacher-Based, Domain-Based Recommenders, Collaborative Filtering	Not specified	Balances precision, recall, and unexpected yet accepted recommendations. Lacks empirical results from actual settings	Effective in personalizing education but faces challenges in integrating multiple recommendation sources and high computational costs

PAPER TITLE	DOMAIN	TECHNIQUE USED / ALGORITMS / Tools	DATASET	EVALUATION OR RESULT	CONCLUSION
23. A Personality-Driven Recommender System for Cross-Domain Learning Based on Holland Code Assessments	Course Selection	Personality-based Collaborative Filtering, Holland Code Test	583 courses from Cheng Shiu University	High student satisfaction (95.54%) with recommendations. Coverage and MAE used to measure effectiveness	Students agree that recommendations align with their interests and future jobs. High user satisfaction confirms system effectiveness
24. A Review on Recommender Systems for Course Selection in Higher Education	Course Selection	Collaborative Filtering (CF), Content-Based (CB), Knowledge-Based (KB), Hybrid Recommender Systems	Literature Review	Identifies hybrid systems as the most effective. Lacks empirical data and practical implementation insights	Ongoing research directions may focus on case studies and technical challenges for implementing recommender systems in educational settings
25. Personalized Course Recommender System based on hybrid approach (PCRS)	Course Selection	Hybrid approach: Content-Based, Collaborative, Knowledge-Based Recommenders, N-gram Query Classification, Ontology	300 courses from BSAR Crescent University	High accuracy (95.25%) and improved precision, recall, and F-measures. No discussion of system limitations or implementation challenges	The hybrid approach enhances personalized recommendations but needs refinement to further improve results
26. Course Enrollment Recommender System (CERS)	Course Enrollment	Data Mining, Collaborative Filtering, Classification, Regression	Data from Masaryk University	S1 (frequent selections) had highest coverage, while S2 (interest-based) had the highest student satisfaction	Effective for improving course selection, with color-coded difficulty predictions. Future work should focus on long-term evaluations of academic performance
27. Recommender System for Elective Course Selection	Course Selection	Collaborative Filtering, Association Rule Mining, K-Means, K-Nearest Neighbors (KNN)	2,000 Electrical Engineering students	High precision (0.95) at the expense of recall. Trade-offs observed between precision and recall	collaborative filtering and association rule mining show potential, they require further improvements to enhance generalizability and resolve the cold start issue
28. Methods for Building Course Recommendation Systems	Learning path Selection	K-Nearest Neighbors (KNN), Matrix Factorization (MF), Biased Matrix Factorization (BMF)	Data from Can Tho University (4017 students, 353 courses, 279,536 grades)	BMF achieved best accuracy (RMSE of 0.831). Needs testing across diverse disciplines	BMF improves course recommendation accuracy, but further validation is needed in different academic settings

PAPER TITLE	DOMAIN	TECHNIQUE USED / ALGORITMS / Tools	DATASET	EVALUATION OR RESULT	CONCLUSION
29. Predicting Student Performance Using Decision Tree Analysis	Student Performance	Decision Trees: J48, Random Tree, REPTree	161 student responses	J48 achieved highest accuracy (0.634). Small sample size limits generalizability	Decision trees are effective in predicting student performance, but future studies should investigate larger datasets and explore more advanced machine learning methods
30. Asian Americans' Career Choices: A Path Model to Examine Factors Influencing Their Career Choices	Career Preference Identificatio n	Social Cognitive Career Theory (SCCT), Path analysis	187 Asian American students from 8 universities	Acculturation impacts career choices, self-efficacy influences interests and decisions, family involvement affects career choice but not self-efficacy	Cultural and familial context is crucial in shaping career choices for Asian Americans, with family expectations often overriding personal interests. Further research on gender, ethnicity, and generational differences is recommended.
31. Course Recommendations in Online Education Based on Collaborative Filtering Recommendation Algorithm	Online Learning, Recommend er Structures	Content-based filtering, Collaborative filtering (user-based, item-based), Pearson's correlation coefficient	Online educational datasets with rich user interaction histories	Improved accuracy and recall rates of course recommendations, particularly for users with rich interaction histories	Promising results in addressing information overload, but future research should explore deep learning models and incorporate implicit feedback to improve accuracy and handle sparse data.
32. Cross-Domain Collaborative Filtering for Recommender Systems	Recommend er Systems	Cross-Domain Collaborative Filtering, Modified Similarity Measures	Amazon dataset (movies, TV, books)	Improved accuracy by reducing sparsity and cold start problem. MAE and RMSE significantly improved compared to traditional CF	Cross-domain similarity enhances collaborative filtering by improving recommendation accuracy in sparse datasets. Further work needed to explore multi-domain use

PAPER TITLE	DOMAIN	TECHNIQUE USED / ALGORITMS / Tools	DATASET	EVALUATION OR RESULT	CONCLUSION
33. Massive open online course recommendation system based on a reinforcement learning algorithm	MOOCs & Online Education	Reinforcement Learning (Actor–Critic Framework)	NTHU MOOCs platform data	Improved engagement and learning outcomes with an ECR of 89.97% and higher midterm scores (64.73 vs 58.21) in the experimental group using the RL-based system.	Reinforcement learning-based recommendation system enhances student engagement and learning in MOOCs. Future studies could focus on improving scalability and integrating more personalized features like real-time feedback.

The paper studies decision tree algorithms (J48, Random Tree, REPTree) for predicting student performance [31]. Analyzing data from 151 participants, it identifies GPA and parental employment as key factors. J48 showed the highest accuracy (True Positive rate: 0.634). While effective, the small sample size limits reliability, highlighting the need for larger studies to enhance accuracy.

The paper explores factors influencing Asian American career choices, such as acculturation, family involvement, socioeconomic status, and self-efficacy [32]. Using Lent et al.'s social cognitive career model, the study analyzes data from 187 college students, emphasizing the role of acculturation and familial expectations. It suggests self-efficacy as key but calls for broader studies to enhance generalizability.

The analysis reveals sparsity and cold start issues in collaborative filtering by integrating user ratings across multiple domains [33]. It proposes a cross-domain similarity measure for personalized recommendations, tested on Amazon datasets, showing improved accuracy over traditional methods. While effective, the study's focus on just two domains suggests potential for broader applications in the future.

The author addresses sparsity and cold start issues in collaborative filtering by integrating user ratings across multiple domains [34]. It proposes a cross-domain similarity measure for personalized recommendations, tested on Amazon datasets, showing improved accuracy over traditional methods. While effective, the study's focus on just two domains suggests potential for broader applications in the future.

The proposed methodology focuses on a MOOC recommendation system using reinforcement learning to personalize exercise recommendations based on learner performance [35]. Integrated with the LINE chatbot, it improved exercise completion rates (89.97% vs. 47.23%) and midterm scores (64.73 vs. 58.21%). Tested on NTHU MOOCs, it showed high user satisfaction, with 90% of students willing to continue using it, offering a scalable learning solution.

The table below (Table 1) provide comparative of the proposed student recommendation system alongside existing recommendation approaches under consistent evaluation criteria.

3. Proposed Framework

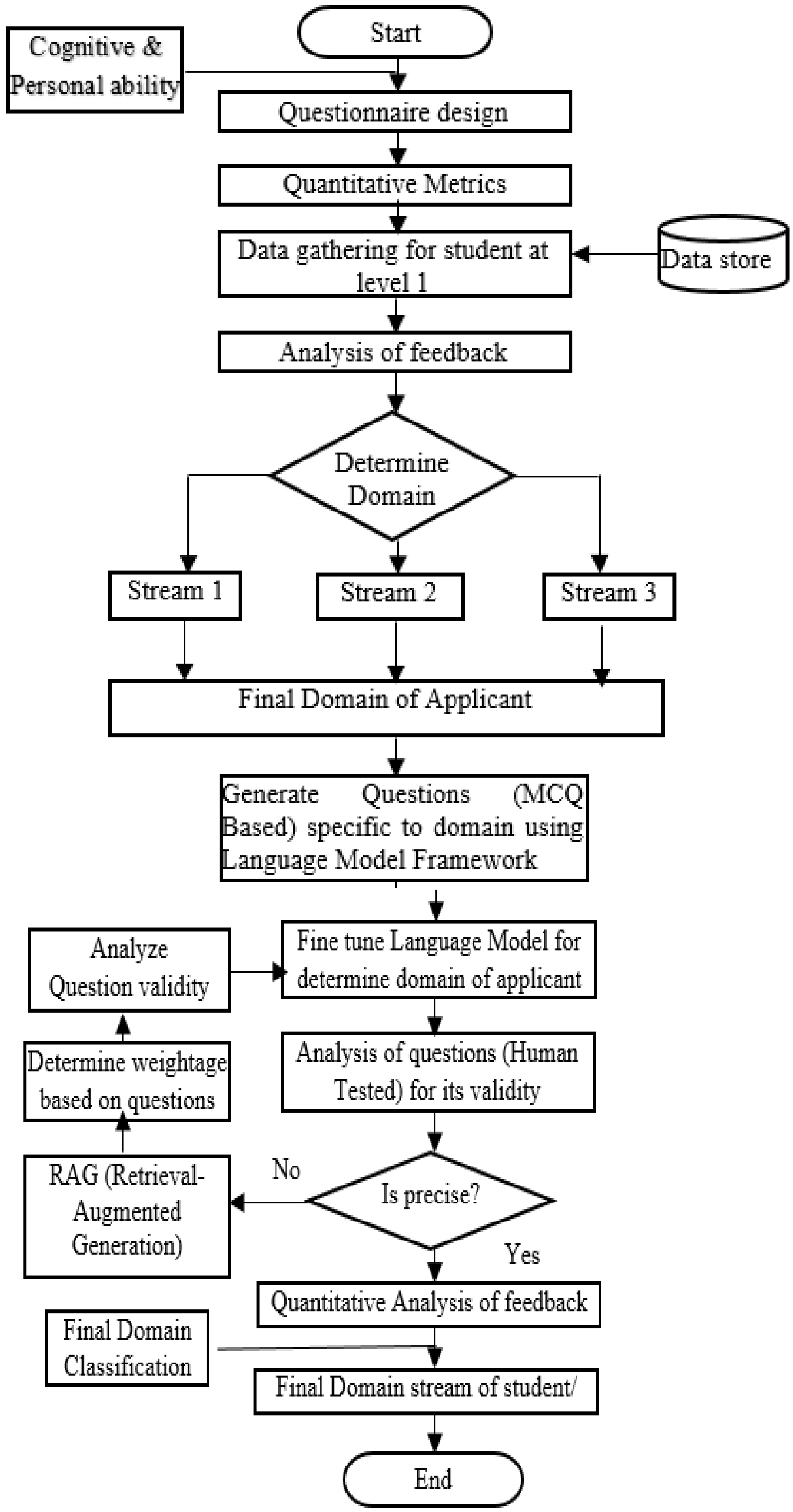

Fig. 5. Proposed Framework for 'An Adaptive AI Framework for Student Domain and Career Guidance'

The proposed Framework shown in Figure 5 for Student Domain and Career Guidanceaims to assist students in selecting suitable academic domains and career paths by analyzing their interests, aptitude, cognitive abilities, and preferences. The overall workflow of the framework is illustrated in Figure 5. The framework operates through three major phases: student profiling and assessment, stream classification, and domain-specific recommendation.

3.1 Student Profiling and Initial Assessment

The first phase focuses on collecting information about the student's interests, strengths, and learning preferences through a structured questionnaire. Sample questions used for assessment are presented in Table 2. These questions evaluate various aspects of student behavior, including analytical thinking, creativity, communication skills, scientific inclination, technological interest, and problem-solving ability.

Table 2: Sample Generalize Questions for Assessment

No.	Questions
1	I enjoy solving complex mathematical problems and equations
2	Understanding how things work mechanically fascinates me
3	Creative writing and artistic expression come naturally to me
4	I find market trends and business news interesting
5	Scientific experiments and laboratory work excite me
6	I am comfortable speaking in front of large groups
7	The human body and its functions fascinate me
8	I am good at analyzing financial data and numbers
9	Understanding human behavior and psychology interests me deeply
10	I feel comfortable working with computers and new technologies

To ensure comprehensive evaluation, a total of 273 questions have been prepared and categorized into four groups: Science, Commerce, Arts, and General Assessment. The distribution of questions across these categories is presented in Table 3. The general questions are intended to assess cognitive and personality traits, while stream-specific questions evaluate academic interests.

Table 3: Stream-Wise Distribution of Questionnaire

Stream	No. of Questions
Arts	51
Science	120
Commerce	63
General	39

Each question is assigned a predefined weight ranging from 0 to 2, as illustrated in Figure 6. Student responses are collected using a five-point rating scale (Table 4) and converted into numerical values for further processing. The collected data are stored and preprocessed to remove inconsistencies and prepare them for classification.

Table 4: Ranking scale

No.	Description	Points (0-2)
1	Strongly agree	1
2	Agree	0.75
3	Neutral	0.50
4	Disagree	0.25
5	Strongly disagree	0

```
"general_questions": [
    {
        "question": "I enjoy solving complex mathematical problems and equations",
        "score_weights": {"science": 2, "commerce": 1, "arts": 0}
    },
    {
        "question": "Understanding how things work mechanically fascinates me",
        "score_weights": {"science": 2, "commerce": 1, "arts": 0}
    },
    {
        "question": "Creative writing and artistic expression come naturally to me",
        "score_weights": {"arts": 2, "science": 0, "commerce": 0}
    },
    {
        "question": "I find market trends and business news interesting",
        "score_weights": {"commerce": 2, "science": 0, "arts": 1}
```


Fig. 6 Quantitative metric, representing question's weightage between (0-2 points)

3.2 Academic Stream Classification

After preprocessing, the framework analyzes the student's responses to identify the most appropriate academic stream. The classification process utilizes the weighted scores obtained from the questionnaire responses.

The stream score is calculated as:

$$\text{Score}\ (S_i) = \sum W_{ij} R_i,\quad j = 1 \text{ to } n$$

Where, $Score_{S_i}$ denotes the cumulative score of the (i^{th}) academic stream,

W_j represents the weight associated with the (j^{th}) questionnaire item,

R_j indicates the response value provided by the student for the (j^{th}) question,

n refers to the total number of questions considered during evaluation.

Based on the cumulative scores, students are classified into one of the major streams (as shown below): Science (ScoreScience), Commerce (ScoreCommerce), or Arts (ScoreArts). This stage narrows the recommendation space and enables a more focused domain-level evaluation.

$$\text{Recommended Stream} = \arg\max(\text{Score}(S_i))$$

3.3 Domain-Specific Assessment

Once the academic stream has been identified, the framework proceeds with a detailed domain-level assessment. Domain-specific questions are selected according to the classified stream to evaluate specialized interests and aptitude.

Table 5: Domain specific Questionnaire Count

Domain	**Question count**	**Domain**	**Question count**
General	15	Creative and design	5
Aeronautical	28	Electrical	18
Architect	26	Engineering	22
Bio technology	26	Environmental Studies	21
Biology	22	Management	34
Chemical	22	Management & Business	5

Domain	Question count	Domain	Question count
Civil	19	Physics	17
Mathematics	23	Research	1
Mechanical	21	Science	4
Medical	34	Librel science	11

The distribution of domain-specific questions is shown in Table 5. These questions cover various disciplines such as Computer Science, Mechanical Engineering, Civil Engineering, Chemical Engineering, Medical Sciences, Electrical Engineering, Environmental Studies, Management, Architecture, and Aeronautical Engineering.

In addition to domain-specific questions, a predefined keyword repository is utilized to identify domain relevance. The keyword distribution for each domain is presented in Table 6. These keywords help establish relationships between student responses and potential academic domains.

3.4 Domain Recommendation Generation

The recommendation engine combines information obtained from the initial assessment, stream classification, domain-specific responses, and keyword matching to determine the most suitable academic domain.

The domain suitability score is computed as:

$$\text{DomainScore}(D_k) = \alpha I_k + \beta A_k + \gamma P_k$$

Where,

Ik = Interest score of the student for domain DkD_kDk

Ak = Aptitude score corresponding to domain DkD_kDk

Pk = Preference score derived from the student's responses

α,mβ and γ = weighting coefficients assigned to interest, aptitude, and preference respectively

The final domain recommendation is determined as:

$$\text{RecommendedDomain}(D^*) = \arg\max(\text{DomainScore}(D_k))$$

Where,

D∗ denotes the recommended academic domain.

argmax, dentifies the domain with the highest suitability score among all candidate domains.

The domain with the highest score is considered the most suitable recommendation for the student.

3.5 Adaptive Questioning and Future Enhancement

The current framework utilizes a structured question repository containing general and domain-specific assessment questions. However, future versions of the system will incorporate adaptive questioning mechanisms using fine-tuned Small Language Models (SLMs) and Large Language Models (LLMs).

The next question will be selected dynamically based on the student's previous response, enabling a more personalized assessment process. Furthermore, Retrieval-Augmented Generation (RAG) techniques will be integrated to retrieve relevant contextual information and generate domain-specific questions in real time. This adaptive approach is expected to improve recommendation accuracy, reduce assessment time, and provide a more interactive counseling experience.

Looking ahead, the framework will transition from a static question set to dynamically generated questions using fine-tuned Small Language Models (SLMs) or Large Language Models (LLMs). These models will allow the system to create real-time, adaptive questions based on a student's live responses and historical data, leading to a more personalized and scalable counseling experience. This dynamic approach will also enhance the system's ability to refine recommendations and adapt to evolving student profiles with greater accuracy and relevance.

4. Conclusion

This research presents an innovative An Adaptive AI Framework for Student Domain and Career Guidance that leverages enhanced machine learning techniques, including all major filtering to streamline academic decision-making. The system follows a three-phase structure—data collection and preprocessing, stream classification, and specialized assessments—which ensures a holistic and personalized counseling approach. Built on fine-tuned Large or Small Language Models (LLMs/SLMs), the framework incrementally improves the quality of its data and recommendations as more student responses are collected over time. To ensure fairness and inclusivity, the model is trained on diverse and balanced datasets representing students from varied backgrounds, and regular bias checks are conducted to maintain equitable outcomes. Designed as a decision-support system rather than a replacement for human judgment, it assists academic counselors by offering data-driven insights into students' interests and strengths, helping to guide accurate domain and career selections. The adaptability of the framework across academic streams and industries, combined with its integration of deep learning algorithms, contributes to improved career satisfaction and reduced mismatches between individual capabilities and professional opportunities. Future improvements may focus on enhancing scalability, incorporating implicit feedback mechanisms, and optimizing computational performance to support broader adoption. Ultimately, this evolving framework holds strong potential to transform modern career counseling by making it more personalized, fair, and responsive to dynamic educational and workforce demands.

Reference

1. What is a recommendation engine and how does it work? Appier. Available at https://www.appier.com/en/blog/what-is-a-recommendation-engine-and-how-does-it-work (accessed Jan 2026)
2. Desai, U.: Recommendation systems explained: From basic to advance. Medium (2021). Available at https://medium.com (accessed Jan 2026)
3. Pham, K.: What are recommendation systems? Medium (2020). Available at https://medium.com (accessed Jan 2026)
4. Pham, K.: Understanding recommendation system algorithms. Medium (2020). Available at https://medium.com/@khang.pham.exxact/what-are-recommendation-systems-6bb5036042db (accessed Jan 2026)
5. Types of recommender systems. Analytics Vidhya (2021). Available at https://www.analyticsvidhya.com/blog/2021/07/ (accessed Jan 2026)
6. Content-based and collaborative filtering. Label Your Data. Available at https://labelyourdata.com/articles/movie-recommendation-with-machine-learning (accessed Jan 2026)
7. Hybrid recommendation system. The Tech Marketer. Available at https://thetechmarketer.com/netflixs-recommendation-engine-a-deep-dive-into-personalization/ (accessed Jan 2026)
8. Application of recommender systems: 10 remarkable real-world examples. Appstek Corp. Available at https://appstekcorp.com/blog/10-remarkable-real-world-examples-of-recommender-systems/ (accessed Jan 2026)
9. The role of recommendation systems in career. International Research Journal of Modern Engineering and Technology (IRJMET) (2023). Available at https://www.irjmets.com/uploadedfiles/paper/ (accessed Jan 2026)
10. Shah, K., Salunke, A., Dongare, S., Antala, K.: Recommender systems: An overview of different approaches to recommendations. In: Proceedings of the International Conference on Innovations in Information Embedded and Communication Systems (ICIIECS) (2017)
11. Chhikara, M., Malik, S.K.: A recommendation system for online social semantic network using knowledge-based, content-based and collaborative filtering. Journal of Information and Optimization Sciences 44(4), 795–806 (2023). https://doi.org/10.47974/JIOS-1356
12. Parvatikar, S., Parasar, D.: Recommendation system using machine learning. In: Proceedings of the International Conference on Recent Advances in Computational Techniques (IC-RACT) (2020)
13. Immanuvel, J., Sheelavathi, A., Priyadharshan, M., Vignesh, S., Elango, K.: Movie recommendation system. International Journal for Research in Applied Science and Engineering Technology (IJRASET) (2021)
14. Bulut, B., Kaya, B., Alhajj, R., Kaya, M.: A paper recommendation system based on user's research interests. In: Proceedings of the IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), Barcelona, Spain (2018)

15. Sharma, J., Sharma, K., Garg, K., Kumar, A.: Product recommendation system: A comprehensive review. IOP Conference Series: Materials Science and Engineering 1022(1), 012021 (2021). https://doi.org/10.1088/1757-899X/1022/1/012021
16. Carrera Rivera, A., Tapia-Leon, M., Lujan-Mora, S.: Recommendation systems in education: A systematic mapping study. Advances in Intelligent Systems and Computing (2018). https://doi.org/10.1007/978-3-319-73450-7_89
17. Shah, P., Munde, S., Farooq, A., Hanamsagar, G., Pagare, R.: Course recommendation system for e-learning. International Journal of Innovative Science and Research Technology 8(5) (2023)
18. Nizam, T., Zafar, S., Hussain, I., Biswas, S.S.: Assessment of recommendation modelling with machine learning. Journal of Information and Optimization Sciences 46(3), 689–715 (2025). https://doi.org/10.47974/JIOS-1680
19. Kolekar, A.: SKYNET: A platform for maximizing career opportunities. In: Proceedings of the International Conference on Nascent Technologies in Engineering (ICNTE) (2021)
20. Lee, D., Kim, M., Na, I.: Artificial intelligence-based career matching. Journal of Intelligent and Fuzzy Systems (2018). https://doi.org/10.3233/JIFS-169846
21. Sundari, M.R., Shreya, G., Jawahar, T.: Course recommendation system. International Journal of Computer Applications 175(29) (2020)
22. de Groot, M., Schutte, J., Graus, D.: Job posting-enriched knowledge graph for skills-based matching. arXiv preprint arXiv:2109.02554 (2021)
23. Koh, M.F., Chew, Y.C.: Intelligent job matching with self-learning recommendation engine. In: Proceedings of the 6th International Conference on Applied Human Factors and Ergonomics (AHFE) (2015)
24. Rasheed, H.A., Weber, C., Harrison, S., Zenkert, J., Fathi, M.: What to learn next: Incorporating student, teacher, and domain preferences for a comparative educational recommender system. In: Proceedings of the 10th International Conference on Education and New Learning Technologies (2018). https://doi.org/10.21125/edulearn.2018.1610
25. Su, J.H., Liao, Y.W., Xu, J.Z., Zhao, Y.W.: A personality-driven recommender system for cross-domain learning based on Holland code assessments. Sustainability 13(7), 3936 (2021). https://doi.org/10.3390/su13073936
26. Lynn, N.D., Emanuel, A.W.R.: A review on recommender systems for course selection in higher education. In: Proceedings of the Annual Applied Science and Engineering Conference (AASEC), Bandung (2020)
27. Gulzar, Z., Leema, A., Deepak, G.: PCRS: Personalized course recommender system based on hybrid approach. Procedia Computer Science 125, 518–524 (2018). https://doi.org/10.1016/j.procs.2017.12.067
28. Bydžovská, H.: Course enrollment recommender system. In: Proceedings of the 9th International Conference on Educational Data Mining (2018)
29. Al-Badarenah, A., Alsakran, J.: An automated recommender system for course selection. International Journal of Advanced Computer Science and Applications 7(3) (2016)
30. Thanh-Nhan, H.L., Nguyen, H.H., Thai-Nghe, N.: Methods for building course recommendation systems. In: Proceedings of the 8th International Conference on Knowledge and Systems Engineering (KSE) (2016). https://doi.org/10.1109/KSE.2016.7758047
31. Hamoud, A.K., Hashim, A.S., Awadh, W.A.: Predicting student performance in higher education institutions using decision tree analysis. International Journal of Interactive Multimedia and Artificial Intelligence 5(2) (2018)
32. Tang, M., Fouad, N.A., Smith, P.L.: Asian Americans' career choices: A path model to examine factors influencing their career choices. Journal of Vocational Behavior 54, 142–157 (1999)
33. Li, J., Ye, Z.: Course recommendations in online education based on collaborative filtering recommendation algorithm. Complexity 2020, Article ID 6619249 (2020). https://doi.org/10.1155/2020/6619249
34. Singh, P.K., Pramanik, P.K.D., Mishra, S., Nayyar, A., Shukla, D., Choudhury, P.: Improving recommendation accuracy using cross-domain similarity. In: Proceedings of the 7th NAFOSTED Conference on Information and Computer Science (NICS) (2020). https://doi.org/10.1109/NICS51282.2020.9335913
35. Tzeng, J.W., Huang, N.F., Chuang, A.C., Huang, T.W., Chang, H.Y.: Massive open online course recommendation system based on a reinforcement learning algorithm. In: Proceedings of the India International Congress on Computational Intelligence (2021), published June 2023