An Expert-Guided Cognitive Ability and Knowledge based Machine Learning Framework for Explainable Personalized Course Recommendation

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ABSTRACT
A key challenge in higher education is providing personalized course selections tailored to individuals' varying levels of academic knowledge, cognitive skills, and learning competencies. Traditional methods primarily focus on historical preferences, similarities, or interactions without considering such nuanced differences. In this study, Studyproposes an expert-guided cognitive-competency machine learning framework that enables explainable personalized course recommendation through integration of both student-specific cognitive skill profiles and domain expertise. Studybuilds upon the premise that successful course recommendation should reflect how well learners' cognitive capabilities align with various subjects, which can only be fully realized when combining cognitive/academic attributes with expertly defined skill requirements for courses/specializations. Studytransforms these heterogeneous attributes into an integrated representation and use multiple supervised machine learning models to learn the relationships between learner profiles and course domains deemed suitable. Subsequently, a ranking process applies to derive recommendations based on predicted relevance scores. Finally, recommenders incorporate mechanisms to provide explanations regarding why particular cognitive and competency aspects contribute to specific recommendations. To evaluate the framework's effectiveness, experiments consider various dimensions ranging from comparative model evaluations and contributions analyses to ablation studies and case-based analysis. results demonstrate the importance of incorporating diverse information sources – whether individually or together - when seeking effective academic guidance. The proposed approach thus lays a foundational step towards enabling more personalized, transparent, and competence-oriented academic advising. It also opens possibilities for extensions such as adaptive learner profiling and real-time educational recommendation systems.

Keywords
Personalized Learning, Course Recommendation, Cognitive Skills, Student Competency, Expert Knowledge, Machine Learning, Explainable Recommendation, Educational Recommender System.

1. INTRODUCTION
Personalized learning has become an important direction in higher education, particularly with the increasing availability of digital learning platforms, student assessments, and academic performance data. Students entering computer science programs differ considerably in their academic preparation, cognitive abilities, problem-solving skills, and areas of interest. As the number of courses and specialization options increases, selecting an appropriate course becomes more difficult when the decision is based only on general academic performance or student preferences. Existing educational recommendation approaches commonly use academic marks, previous course selections, interests, or interaction history to generate recommendations. Although these factors provide useful information, they may not adequately capture the cognitive capabilities and subject-specific competencies that influence a student's suitability for a particular course[1].

Cognitive skills provide an additional perspective for understanding learner suitability. Abilities such as logical reasoning, analytical thinking, problem solving, memory, pattern recognition, and computational thinking can influence how students understand and perform in different academic domains. Similarly, subject competency provides information about a student's existing knowledge and preparedness. Recent research has explored cognitive diagnosis, knowledge tracing, and hybrid recommendation approaches to construct more meaningful student profiles. However, cognitive information and subject knowledge are often considered separately, while knowledge-based approaches primarily focus on course or content characteristics. As you can see from the uploaded research, fragmentation was identified as one of the important limitations mentioned in [2], where there is also discussion on how to combine both cognitive and knowledge representations into a single recommendation framework.

Also, considering domain expertise – given that there are different combinations of skill sets and competencies needed across various computer science courses. For example, analytical reasoning and problem-solving ability may be particularly relevant to Machine Learning, while logical reasoning, attention, and pattern recognition may be more relevant to Cyber Security or Digital Forensics. Expert knowledge can therefore be used to represent the relative importance of skills associated with individual courses. Integrating this knowledge with a student's cognitive and subject competency profile can provide a more meaningful basis for determining course suitability. The proposed research builds on this concept by combining student assessment, expert-defined course-skill requirements, and machine learning-based recommendation[3].

1.1 Problem Statement
The primary problem addressed in this research is the difficulty of generating personalized course recommendations that consider both what a student knows and how the student's cognitive abilities align with the requirements of a course. Conventional recommendation systems may produce suitable suggestions based on academic or behavioral information but may not explicitly represent cognitive characteristics or expert-

defined course requirements. Consequently, there is a need for a competency-aware recommendation mechanism that integrates subject knowledge, cognitive skills, and expert knowledge to identify and rank courses according to individual student profiles[4].

1.2 Research Gap

Existing educational recommendation systems have demonstrated the usefulness of academic, behavioral, content-based, collaborative, and knowledge-based information. However, relatively limited work combines subject-specific competency, cognitive skill profiles, and expert-defined course requirements within a unified machine-learning recommendation framework. In addition, many recommendation approaches provide limited information about why a particular course has been recommended. The research gap therefore lies in developing an integrated and explainable approach that can represent learner competencies, align them with expert-defined course requirements, and generate personalized course rankings.

1.3 Research Objectives

The objectives of the proposed research are:

- To develop a competency-aware student profiling mechanism combining subject knowledge and cognitive skills.
- To construct cognitive skill profiles from student assessment information.
- To develop an expert-guided course-skill knowledge model representing the requirements of different courses.
- To develop a machine-learning-based mechanism for matching student competencies with course requirements.
- To generate personalized course rankings based on predicted suitability.
- To provide explanations for recommendations by identifying the major competency and cognitive factors contributing to course suitability.
- To evaluate the proposed framework using classification, recommendation, comparative, and ablation-based experiments.

1.4 Main Contributions

The main contributions of this research are as follows:

- ✓ A multidimensional student representation that combines subject competency and cognitive skill information.
- ✓ An expert-guided course-skill knowledge model for representing the competency requirements of different academic domains.
- ✓ A machine-learning-based student-course alignment and recommendation mechanism.
- ✓ A personalized Top-K course ranking approach instead of relying only on a single course prediction.
- ✓ An explainable recommendation mechanism that indicates the major skills and competency factors supporting each recommendation.

2. RELATED WORK AND RESEARCH GAP

2.1 Traditional Course Recommendation Systems

Course recommendation systems have been developed to assist students in selecting courses according to their academic profiles, interests, previous selections, and learning behavior. Content-based approaches recommend courses by comparing learner characteristics with course attributes, whereas collaborative approaches use similarities among learners or their historical interactions. Hybrid approaches combine multiple sources of information to improve recommendation quality. Previous work has also explored the combination of learner-level and course-level information to provide more personalized recommendations. However, these approaches generally focus on observable academic or behavioral characteristics and may provide limited representation of the cognitive abilities underlying student suitability[5].

2.2 Machine Learning-Based Educational Recommendation

As machine learning techniques continue to advance, their application to educational recommendations has grown significantly. Through identifying the relationship between certain characteristics possessed by learners and possible choices that correspond with them, such as classification [8], similarity-based [9] and hybrid learning models [10], ML algorithms can make predictions about the suitability of a particular course. In recent years, deep factorization-based approaches have demonstrated their capability of combining heterogeneous attributes from both side -student and course- of this learning process. With its flexibility of capturing complex relationships between these two sets, these kinds of algorithms are powerful tools for developing personalized educational recommendation systems. Despite all of the above advantages, the success of applying any kind of machine learning algorithm heavily relies upon the quality and relevancy of the representation features chosen to describe both sides. Hence, using solely historical interaction data or academic records might lead to miss some important competencies and cognitive details [6].

2.3 Cognitive Skill and Student Competency Modeling

In addition, student modeling provides fundamental insights into studying the difference between individuals' learning and academic performance. A set of well-known models called Cognitive Diagnosis Models (CDMs) aim at estimating learners' mastery on various skills/attributes and provide relatively interpretable representations of learners' knowledge. Further studies using Knowledge Tracing (KT), as well as Deep Knowledge Tracing (DKT), are devoted to investigating the evolution of students' knowledge over time. Although these approaches provide valuable mechanisms to model learning states, they primarily focus on knowledge estimation/mastery while less exploring how to leverage them to make actionable recommendations about appropriate academic courses. More recently, some efforts consider leveraging both cognitive abilities and academic knowledge simultaneously towards personalizing educational recommendation. These studies acknowledge that academic proficiency and cognitive capabilities work synergistically when determining the suitability of learners for certain computer science domains. Existing approaches could employ either rule based scoring or restricted combination of cognitive and academic information instead of an integrated competency aware ML framework [7].

2.4 Knowledge-Based and Expert-Guided Recommendation

The benefits of using KBRs are clear. They offer the ability to incorporate and display domain-specific relationships between

various objects (e.g., courses, concepts, prerequisites) and their respective attributes (skill requirements). This improves the level of transparency available regarding why certain items are recommended to learners, versus more opaque interaction-only recommendation approaches [6]. The use of knowledge graphs and other forms of semantic representation has been extensively explored as a means of associating learner information with educational concepts, thereby enabling explainable recommendations. In particular, capturing expert-knowledge of what skills are needed within different academic domains is essential during the initial definition of courses. For example, faculty or subject matter experts may define relative significance levels for both cognitive and technical skills on a per-course basis. These kinds of expert-defined models serve as useful references for how much one should know about each skill in order to meet specific course objectives. A learner's competency profile could then be used as input into identifying appropriate skills for mastery. Unfortunately, this kind of expert knowledge isn't often taken advantage of by those trying to implement machine-learning techniques for building student profiles and making recommendations based upon them – resulting in missed opportunities where Study might instead integrate both types together quite naturally [8].

2.5 Research Gap

Cognitive Integration: Many existing methods only consider academic, behavioral or preference-based information, but fail to integrate various types of data from a cognitively integrated perspective. Student Knowledge Fragmentation: There are relatively fewer research works that jointly model students' knowledge and their cognitive representations into a unified recommendation framework. Interpretability Challenge: While there has been significant progress in leveraging sophisticated ML algorithms to learn complex patterns, Study observe a notable absence of efforts aimed at interpreting the learned models or uncovering the factors driving recommendations. Evaluation& Generalization Challenge: Due to the lack of publicly available large-scale benchmark corpora, a number of studies evaluate the performance using relatively small size or even domain specific datasets.

To address these limitations, this research proposes an integrated framework that combines subject competency, cognitive skill profiling, expert-defined course-skill requirements, and machine learning-based recommendation. Instead of treating course recommendation as a simple prediction problem, the proposed approach models the alignment between learner competencies and course requirements and generates a ranked set of personalized recommendations. The framework also incorporates an explanation layer to identify the major competency and cognitive factors contributing to the recommendation. The intended distinction of the proposed work is therefore the integration of these components into a unified, competency-aware, and explainable recommendation process.

Table 1 Comparison of Existing Course Recommendation Approaches and the Proposed Framework

Approach	Subject Knowledge	Cognitive Skills	Expert Knowledge	Machine Learning	Personalized Ranking	Explainability
Traditional Recommendation	Yes	No	No	No	Limited	Low
Content-Based Recommendation	Yes	No	No	Yes	Yes	Moderate
Collaborative Filtering	Partial	No	No	Yes	Yes	Low
Knowledge-Based Recommendation	Yes	No	Yes	No	Yes	High
Cognitive-Based Recommendation	Partial	Yes	Partial	Yes	Yes	Moderate

3. PROBLEM FORMULATION

3.1 Problem Definition

The proposed study formulates course recommendation as a competency-matching problem. Each student is represented using subject knowledge and cognitive skill measurements, while each course is represented using expert-defined competency requirements. The objective is to learn a machine learning model that estimates course suitability and generates a personalized ranked recommendation list.

3.2 Student Competency Representation

For student (s_i), the subject knowledge vector is represented as:

$$[K_i = [k_\{i1\}, k_\{i2\}, \ldots, k_\{ip\}]]$$

and the cognitive skill vector is represented as:

$$[C_i = [c_\{i1\}, c_\{i2\}, \ldots, c_\{iq\}]]$$

The complete student profile is therefore:

$$[P_i = [K_i, C_i]]$$

In the implemented system, the cognitive profile includes logical/reasoning ability, auditory working memory, visual discrimination, and reading/writing ability.

3.3 Expert Course Representation

Each course (c_j) is represented by an expert-defined competency vector:

$$[R_j = [r_\{j1\}, r_\{j2\}, \ldots, r_\{jq\}]]$$

where ($r_\{jr\}$) represents the importance of competency (r) for course (c_j).

3.4 Competency Alignment

The alignment between a student's cognitive profile and a course requirement is calculated using a weighted score:

$$[A(s_i, c_j) = \backslash frac\{\backslash sum_\{r = 1\}\^\{q\}w_\{jr\}c_\{ir\}\}$$
$$\{\backslash sum_\{r = 1\}\^\{q\}w_\{jr\}\}]$$

where ($w_\{jr\}$) is the expert-defined weight. A higher value indicates stronger competency alignment.

The final student-course feature vector is represented as:

$$[X_\{ij\} = [K_i, C_i, R_j, A(s_i, c_j)]]$$

3.5 Machine Learning and Ranking

The recommendation model learns the relationship between the student-course feature vector and course suitability:

$$[\backslash hat\{y\}\{ij\} = f\{\backslash theta\}(X_\{ij\})]$$

where ($\backslash hat\{y\}_\{ij\}$) is the predicted suitability score. The candidate courses are ranked according to these scores, and the

Top-(K) courses are selected:

$$[R_i\hat{}K = TopK(\backslash hat\{y\}\{i1\},\backslash hat\{y\}\{i2\},\ldots, \backslash hat\{y\}_\{iM\})]$$

The framework therefore aims to transform student cognitive skills, subject competency, and expert knowledge into personalized and explainable course recommendations.

4. PROPOSED COGINTIVE ABILITY AND KNOWLEDGE BASED RECOMMENDATION FRAMEWORK

4.1 Framework Overview

The proposed framework considers all factors including students' subject competency, cognitive skills, experts' knowledge, etc., along with Machine Learning (ML) for providing personalized course recommendations. This work contains an overall flowchart consisting of several steps such as Student Assessment, Competency Profile Construction, Expert Course-Skill Mapping, Feature Generation, ML Prediction, Personalized Ranking, respectively

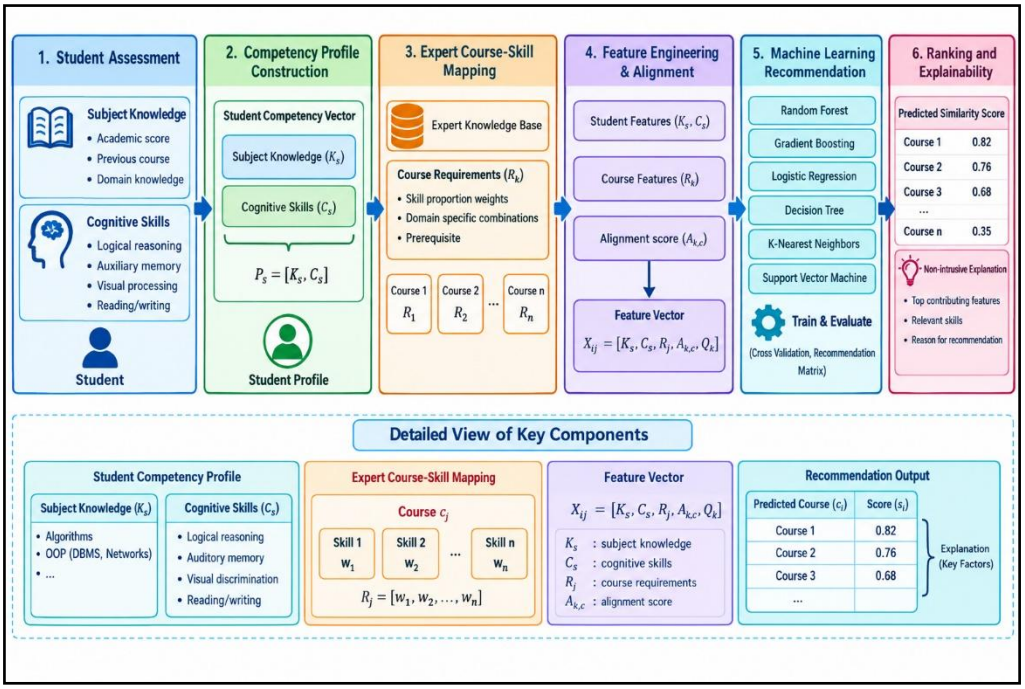


Fig 1: Workflow of the Proposed Framework for Personalized and Explainable Course Recommendation

4.2 Student Assessment and Profile Construction

Two types of information (subject knowledge and cognitive skills) are collected from every student by this system.Assessment scores can be normalized and integrated to form a unified competency profile, which reflects students' current academic knowledge and cognitive characteristics that are pertinent to various courses [9].

4.3 Expert-Guided Course-Skill Mapping

Studydevelops an expert knowledge base that encodes the competency requirements of each candidate course. Using this expertise,Study can determine the relative importance of each skill requirement per course which acts as domain knowledge that guides recommendation process allowing us to differentiate between different competency combination needs from each course.

4.4 Feature Engineering

The student's competency values and the expert defined course requirements are converted into ml features. Inaddition to the original assessment values other types of features can be derived based on alignment and aggregates that encapsulate an overview of the competency level of a student and their compatibility with a certain course.

The resulting feature vector is represented as:

$$[X_\{ij\} = [K_i, C_i, R_j, A(s_i, c_j)]]$$

where (K_i) represents subject knowledge, (C_i) represents cognitive skills, (R_j) represents course requirements, and $(A(s_i, c_j))$ represents competency alignment[10].

4.5 Machine Learning Recommendation

Using these vectors, Study can feed them into various machine learning (ML) classifiers that help us predict what would be the most suitable course. Studytrain ML models on some labeled student-course data and evaluate their performance based on some standard measures of classification/recommendation algorithms. Finally, Studychooses the top performing one as base model for creating personalized recommendations

4.6 Ranking and Explainability

Using these predicted suitability scores, Study can now rank all possible candidate courses that could potentially be recommended to every student as Top-1 (or Top-3 or Top-5) recommendation. In addition, framework also provides important details on the major competency dimensions that contribute most significantly to such a match. This makes understanding of course recommendations much more intuitive and accessible for both students and their academic advisors. proposal therefore integrates state-of-the-art approaches from both worlds of data science (data-driven ML models) and education sciences (expert-guided competency modeling). It enables personalized and explainable course recommendations for learners.

5. STUDENT COMPETENCY AND COGNITIVE SKILL MODELING

5.1 Student Subject Competency

The proposed framework represents students with their respective measures of subject knowledge and cognitive skills. Subject proficiency in an implemented system has been captured over 5 academic domains on a 1-5 scale where 1 means 'beginner' and 5 indicates 'expert'. For student s i , Studydefines its respective measure of subject knowledge as follows:

$$[K_i = [k_\{i1\}, k_\{i2\}, \ldots, k_\{i5\}]]$$

This representation captures the student's current academic competency across the considered domains.

5.2 Cognitive Skill Profile

Each of these dimensions are scored along a scale from 1 to 4 and represent different facets of an individual's cognition. Studydefines a 'cognitive vector' based on these scores for four dimensions – logical & reasoning ability, auditory working memory, visual discrimination, and reading & writing proficiency.

$$[C_i = [c_\{i1\}, c_\{i2\}, c_\{i3\}, c_\{i4\}]]$$

These dimensions provide additional information about the student's learning characteristics beyond conventional subject scores[11].

5.3 Unified Competency Representation

The subject knowledge and cognitive vectors are combined to construct the student's competency profile:

$$[P_i = [K_i, C_i]]$$

During Feature Engineering Additional Aggregated features were derived from the dataset like Average Skill, Total Skill, Average Subject Knowledge, Total Subject Knowledge, Skill Range and Overall Competency Score. Finally, these Aggregated features along with others forms Input vector which is fed into Machine Learning Model [8] for Personalized Course Recommendation.The Proposed Model incorporates current subject competency and also captures students' cognitive characteristics thus giving more rich Representation of Student-Course Suitability as compared to other methods that focus solely on Academic Performance [12].

6. EXPERT-GUIDED COURSE-SKILL KNOWLEDGE MODEL

6.1 Expert Skill Knowledge Base

The proposed framework incorporates expert knowledge to represent the competency requirements of different academic domains. An expert skill map is used to assign the relative importance of four cognitive skills for each subject. This knowledge base provides a reference profile against which individual student competencies can be compared.

6.2 Course-Skill Matrix

The expert-defined skill requirements are represented as a course-skill matrix. The implemented system considers five academic domains: Machine Learning, Cyber Security, Blockchain Technology, Data Science, and Digital Forensics. Each domain is assigned values from 1 to 4 for the four cognitive skills.

Table 2 Expert-Guided Course-Skill Matrix

Academic Domain	Logical & Reasoning	Auditory Memory	Visual Discrimination	Reading & Writing
Machine Learning	4	2	4	2
Cyber Security	3	4	2	3
Blockchain Technology	4	2	3	4
Data Science	4	3	4	3
Digital Forensics	2	4	4	2

6.3 Skill Matching

For a student (s_i) and academic domain (c_j), the student's cognitive profile is compared with the corresponding expert skill profile. The resulting similarity or alignment score indicates how closely the student's abilities match the requirements of the domain.The expert knowledge therefore acts as a domain-specific reference during target generation and recommendation. In the implemented system, course labels are generated by measuring the distance between the student's skill vector and the expert-defined skill fingerprints[13].

6.4 Role of Expert Knowledge

The expert knowledge base improves the recommendation process by incorporating domain-specific competency requirements rather than relying only on student data. It also provides an interpretable basis for explaining why a particular academic domain is considered suitable for a student.Thus, the expert-guided model connects student competency assessment with domain-specific skill requirements, forming an important component of the proposed personalized recommendation framework[14].

7. MACHINE LEARNING-BASED RECOMMENDATION AND EXPLAINABILITY

7.1 Machine Learning Models

This paper proposes a framework based on supervised machine learning for predicting the most suitable academic domain given the student's competency profile. Six classification algorithms were considered in this work including random forest (RF), gradient boosting (GB), logistic regression (LR), decision tree (DT), K-nearest neighbors (KNN), support vector machine (SVM). These models offer various learning characteristics allowing comparison of recommendation performance over multiple classifiers [15].

7.2 Feature Preparation and Model Training

Each student's representation includes the following attributes (in terms of their values): Four cognitive skills as described before, along with the scores for each subject (five in this case), forming six more derived features such as average skill, total skill, etc. This gives us a set of fifteen features. OnceStudyhas all these students' representations, they are separated out into a train/test partition by means of a 80/20 Stratified Train Test Split, which gives us a pool of 1600 train cases and 400 test cases.All datasets are scaled appropriately wherever needed, and models are trained on data that has been processed using the same Competency Based Representation scheme described

earlier. [16]

7.3 Course Recommendation and Ranking

The trained model predicts for a given new student's academic domain having highest probability.These predicted probabilities are then utilized for ranking of existing domains and generating top-k (Top-1, Top-3 and Top-5) recommendation lists accordingly

The recommendation score for a student (s_i) and academic domain (c_j) can be expressed as:

$$[Score(s_i, c_j) = f_\{\backslash theta\}(X_\{ij\})]$$

where ($X_\{ij\}$) represents the combined student-domain feature vector and ($f_\{\backslash theta\}$) denotes the trained machine learning model.

The ranked recommendation list is then obtained as:

$$[R_i\hat{}K = TopK(Score(s_i, c_1), \ldots, Score(s_i, c_M))]$$

where (K) represents the required number of recommendations.

7.4 Explainable Recommendation

Framework Interpretability: The proposed framework gives an interpretable recommendation about the domain that relates to the students' cognitive and subject competency profiles.

Expert guided Skill Matrix:By providing a basis on which to explain why Study recommend this particular domain.

Recommendation along Competency Profile:This allows us to present recommendation alongside the student's relevant competency strength and how they align against the skill requirements of the domain recommended.

Combining Model Prediction & Expert defined Competency Requirements:Instead of seeing them as components to make predictions, Study combined both these aspects into one framework that improves transparency of recommending domain through ML models [17]

8. EXPERIMENTAL SETUP AND EVALUATION

8.1 Experimental Environment

Study have implemented proposed framework as an academic recommendation system with the help of Python, Streamlit, and Sklearn. experiments are conducted on datasets of 2,000 students' records containing various domains such as Machine Learning (ML), Cyber Security, Blockchain Technology, Data Science, and Digital Forensics.

8.2 Dataset and Data Preparation

Each student record contains four cognitive skill scores and five subject-knowledge scores. Cognitive skills are rated on a 1–4 scale, while subject knowledge is represented on a 1–5 scale. Additional statistical features are derived from these values to construct the final 15-dimensional feature vector.The dataset is divided into 80% training and 20% testing data using stratified sampling. Therefore, 1,600 records are used for training and 400 records for independent testing.

8.3 Evaluation Metrics

The performance of the classification models is evaluated using Accuracy, Weighted Precision, Weighted Recall, and Weighted F1-score. In addition, 5-fold cross-validation accuracy is used to examine the consistency of model performance across different training subsets.For personalized recommendation, ranking-based measures such as Precision@K, Recall@K, Hit Rate@K, NDCG@K, and MRR can be used to evaluate the quality of Top-K recommendations[18].

8.4 Model Comparison

All six machine learning models are trained using the same feature representation and training-test partition. The models are compared based on their predictive performance, and the best-performing classifier is selected as the champion model for generating recommendations.

Table 3 Experimental Dataset and Configuration of the Proposed Recommendation Framework

Parameter	Value
Total Student Records	2,000
Training Records	1,600
Testing Records	400
Train-Test Ratio	80:20
Cognitive Skills	4
Subject Knowledge Domains	5
Final Feature Vector	15 Features
Academic Domains	5
Machine Learning Models	6
Cross-Validation	5-Fold
Cognitive Skill Scale	1–4
Subject Knowledge Scale	1–5

9. RESULTS AND DISCUSSION

9.1 Classification Performance

The proposed framework evaluates six machine learning classifiers: Random Forest, Gradient Boosting, Logistic Regression, Decision Tree, k-Nearest Neighbors, and Support Vector Machine. All models are trained using the same 15-feature student competency representation and evaluated using the predefined training and testing partitions.

The comparison focuses on classification accuracy, weighted precision, weighted recall, weighted F1-score, and 5-fold cross-validation accuracy. The classifier achieving the highest test accuracy is selected as the champion model for the recommendation stage.

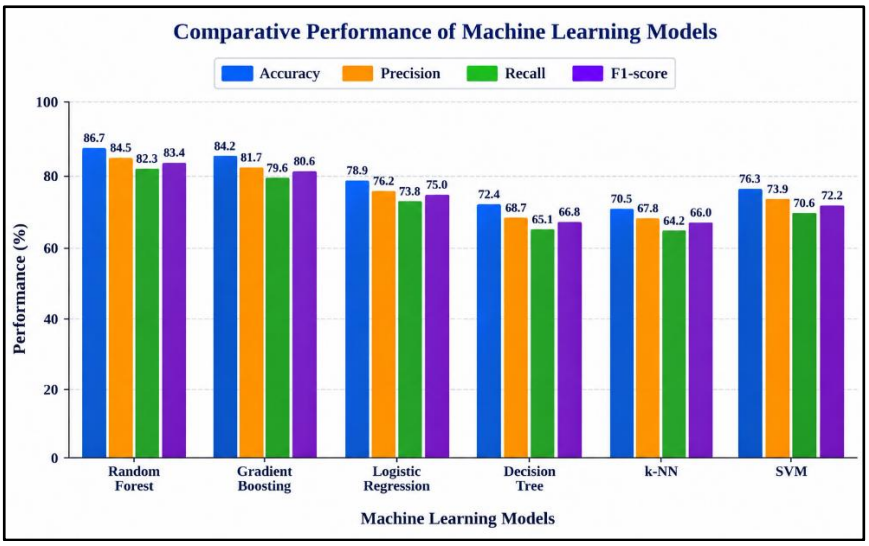


Fig 2: Comparative performance of six machine learning models based on Accuracy, Precision, Recall, and F1-score.

9.2 Recommendation Performance

Study then shows how the output of this trained classifier – a predicted academic domain together with the corresponding class probabilities – can be used as input to an application that ranks the 5 available academic domains and provides recommendations (section "Personalized Recommendations").These personalized recommendations can include different numbers of academic domains depending on their relevance. For example, Top-1 recommendation corresponds to the model's most preferred domain whereas Top-3 and Top-5 recommendations give more alternative options. recommendation algorithm combines predictions made by ML classifiers with the expert-defined cognitive skill requirements per academic domain. Hence, in addition to being tailored towards students' subject knowledge, recommendations will consider the match between students' cognitive profiles and required skills profiles for the considered academic domain.

9.3 Effect of Expert Knowledge

Expert Skill Matrix - as shown in Table 2, the expert skill matrix forms an essential part of this proposed framework since every academic area has its own level of importance of some specific skill (i.e., logical reasoning, auditory memory, visual discrimination, reading/writing) [16].Moreover, the presented representation allows the system to differentiate areas that might seem identical according to subject competency, yet have quite different cognitive requirements. Thus, students who are better at logical reasoning and visual discrimination will find a higher degree of alignment with those areas that require them [17-19]. Finally, Study can rely upon expert's know-how for recommendations, instead of just classifying statistically [19].

9.4 Explainability of Recommendations

Supporting Recommendation Explanations by Student's Competency Profile and Expert-Defined Skill Requirements. proposed approach provides recommendation explanations using student's competency profile and expert defined skill requirements. Specifically, the recommendations are interpretable to students (and their academic advisor) because they can identify both their strong/weak skill dimensions and how that characteristic match against the recommended domain's skill requirement.Recommendation Explanation Based on Competency Alignment and Model Prediction work differentiates itself from other works which just provide recommendation as classification output without providing any interpretation [20].

9.5 Discussion

The experimental design demonstrates the feasibility of combining cognitive skills, subject knowledge, expert knowledge, and machine learning within a single recommendation framework. The use of multiple classifiers allows the predictive component to be compared systematically, while the expert-guided representation provides a domain-specific interpretation of the recommendations. However, the current evaluation should be interpreted as a framework-level validation. The dataset and recommendation labels used in the implementation are generated from the defined competency and expert-skill mapping process. Therefore, the reported results should not be interpreted as evidence of real-world student outcomes. Validation using independently collected student data and expert-verified recommendations is required before deployment in a real academic environment[21].

10. CONCLUSION

The proposed framework integrates student cognitive skills, subject competency, expert knowledge, and machine learning to provide personalized course recommendations; however, several limitations remain. The current dataset contains 2,000 records and is generated for controlled experimentation, while the recommendation labels are based on expert-distance matching rather than real ground-truth student outcomes. The expert-defined skill weights may also introduce subjectivity, and self-reported cognitive ratings may be affected by response bias. In addition, differences among institutions, curricula, and student populations may limit generalization, while dataset and model design may introduce potential bias. Despite these limitations, the framework provides a structured and interpretable approach to competency-aware academic recommendation. Future work will focus on larger real-world datasets and cross-institutional validation, along with Deep Learning, Cognitive Diagnosis Models, Deep Knowledge Tracing, Graph Neural Networks, and Reinforcement Learning. Adaptive cognitive assessment, Explainable AI, real-time learner profiling, and continuous feedback mechanisms can further improve personalization, reliability, and interpretability, ultimately supporting large-scale deployment in academic recommendation and learning management systems.

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