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A Competency-Aware Machine Learning Framework for Personalized Course Recommendation Using Cognitive Skills and Expert Knowledge

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Abstract: Personalized course selection has become increasingly important in higher education as students are presented with a growing range of courses and specialization options. Conventional recommendation approaches generally rely on academic performance, previous course choices, or stated preferences, which may not adequately capture the cognitive abilities and subject specific competencies required for successful learning. This paper proposes a competency aware machine learning framework for personalized course recommendation that integrates student subject knowledge, cognitive skills, and expert defined course requirements. The proposed framework first constructs an individual student competency profile by combining subject level knowledge assessment with cognitive skill assessment covering dimensions such as logical reasoning, analytical thinking, problem solving, pattern recognition, and computational thinking. In parallel, domain experts define the relative importance of these skills for different courses through a course skill knowledge model. The resulting student and course representations are used to determine competency–course alignment and generate personalized recommendation scores. Machine learning models are then employed to learn the relationship between student characteristics and suitable course choices, while an explainable recommendation component identifies the skills contributing to each recommendation. The framework is evaluated against progressively enriched baseline models using both predictive and recommendation-oriented measures, including accuracy, precision, recall, and F1 score, Precision@K, Recall@K, NDCG@K, and MRR. An ablation analysis is further used to examine the con attribution of cognitive skills, subject competency, and expert knowledge. The proposed approach aims to provide recommendations that are not only personalized but also competency aligned and interpretable, thereby supporting more informed course selection in computer science education.

Keywords: Personalized course recommendation, machine learning, competency modeling, cognitive skills, expert knowledge, explainable recommendation, and higher education.

1. INTRODUCTION

The rapid growth of digital learning platforms has made a wide range of courses available to students, but at the same time it has made course selection increasingly difficult. A student may have access to hundreds of courses, while their actual learning needs may depend on their existing knowledge, academic performance, skills, interests, and ability to understand different levels of concepts. In many educational platforms, course recommendations are generated mainly from previous enrollments, ratings, course similarity, or the behavior of other learners. Although these approaches are useful for identifying general preferences, they do not always reflect whether a particular student has the required competency to successfully undertake a recommended course. This creates a need for recommendation approaches that consider the learner as an individual rather than treating similar users as having similar learning requirements[1].

Machine learning has provided several opportunities to improve personalized learning by identifying patterns in learner data and predicting courses that may be relevant to individual students. However, the effectiveness of a recommendation depends strongly on the information used to represent both the learner and the course. Academic scores or past course selections alone may not adequately describe a student's actual competency. In particular, different courses may require different levels of cognitive skills such as remembering, understanding, applying, analyzing, evaluating, and creating. A student who has completed a prerequisite course may therefore still require a different learning path depending on their demonstrated competencies and cognitive abilities. Incorporating these aspects into a recommendation system can provide a more meaningful connection between what a learner already knows and what the learner is expected to achieve through a particular course[2].

Another important consideration is the role of expert knowledge in educational decision making. Experienced teachers and subject experts can identify prerequisite relationships, competency requirements, difficulty levels, and cognitive expectations that may not be directly visible in historical student data. Purely data driven models may perform well when sufficient and reliable training data are available, but their recommendations can become less reliable when data are limited, incomplete, or biased toward previously observed behavior. Combining expert knowledge with machine learning can therefore provide an opportunity to use both empirical patterns and pedagogical understanding in the recommendation process. Such an approach can also make the recommendation process easier for educators to understand and evaluate[3].

Despite the development of several personalized learning and course recommendation systems, there remains a gap in integrating learner competency, cognitive skills, course requirements, and expert knowledge within a common recommendation framework. Existing approaches often concentrate on learner preferences or interaction history, while the relationship between a learner's current competency and the cognitive requirements of a course receives comparatively less attention. This limitation can lead to recommendations that are relevant from a behavioral perspective but may not necessarily represent the most appropriate learning progression for the student. Therefore, a competency aware recommendation mechanism is required to establish a stronger relationship between learner characteristics and course requirements[4].

To address this issue, this study proposes a Competency Aware Machine Learning Framework for Personalized Course Recommendation Using Cognitive Skills and Expert Knowledge. The proposed framework considers the competency profile of a learner together with cognitive skill requirements and relevant course characteristics, while incorporating expert knowledge into the recommendation process. The objective is to identify courses that are not only related to a student's interests or previous learning behavior but are also aligned with the learner's current capabilities and expected learning requirements. The framework is intended to support more personalized and meaningful course selection while providing an approach that can be evaluated using measurable machine learning and recommendation performance indicators[5].

The major contribution of this research is the development of a unified approach that connects learner competency, cognitive skills, course requirements, and expert knowledge within a machine learning-based recommendation process. The study further investigates how these factors can be represented and combined to improve the relevance of recommended courses. By incorporating pedagogical knowledge alongside data driven learning, the proposed approach aims to address some of the limitations of conventional recommendation techniques and provide a more suitable basis for personalized educational pathways[6].

2. RELATED WORK AND RESEARCH GAP

Course recommendation has been studied as a way of helping learners identify suitable courses from a large and continuously growing set of educational resources. Early course recommendation systems generally relied on collaborative filtering, content-based filtering, or a combination of both approaches. Collaborative filtering recommends courses by identifying similarities between learners based on their previous course selections, ratings, or interactions, whereas content-based methods use course descriptions, topics, prerequisites, and other attributes to identify courses similar to those already preferred by a learner. These approaches have provided a useful foundation for educational recommendation; however, they are largely dependent on historical behaviour and course level similarity. As a result, a recommendation may appear relevant based on previous interactions without necessarily considering whether the learner possesses the competencies required for the recommended course[7].

The increasing availability of learner data has encouraged the use of machine learning techniques for educational recommendation. Classification, clustering, decision trees, nearest neighbor methods, and other predictive approaches have been explored to identify learner preferences, predict course selection, and personalize learning paths. More recent systems also consider academic performance, learner profiles, interaction history, and course characteristics while generating recommendations. Machine learning provides an advantage over purely rule based systems because it can discover relationships within learner data that may not be explicitly defined. Nevertheless, the quality of such recommendations depends on the characteristics and completeness of the available data. A model trained mainly on historical enrolment or interaction patterns may reproduce existing preferences without adequately identifying the skills a learner needs to develop next.

Competency based education provides a different perspective by focusing on what a learner is able to demonstrate rather than only on course completion or academic performance. Competencies can represent a combination of knowledge, skills, and abilities that a learner is expected to acquire through an educational Programme. From a recommendation perspective, competency information can help determine whether a learner is adequately prepared for a particular course and can also identify areas where further learning is required. However, competency-based information has not always been incorporated directly into conventional recommendation models. Many existing systems continue to treat the learner primarily through ratings, preferences, or historical activities, leaving the relationship between the learner's current competency and the competency requirements of a course insufficiently explored[8].

Cognitive skills are another important dimension of personalized education. Learning activities and courses may require students to perform different levels of cognitive processes, ranging from basic understanding of concepts to application, analysis, evaluation, and creation. Assessing these skills can provide additional information about how a learner may respond to a particular course or learning activity. When cognitive requirements are associated with course content, recommendations can potentially be made according to both the learner's existing competency and the level of cognitive ability required for successful learning. Despite its importance in educational assessment, cognitive skill information is not commonly integrated with course recommendation in a unified manner, particularly in systems that also consider competency and expert knowledge.

Expert knowledge can help address some of the limitations associated with purely data driven recommendation. Teachers and subject experts possess knowledge about course prerequisites, relationships among subjects, expected competency levels, course difficulty, and the cognitive skills required to understand particular topics. This knowledge can be represented through rules, competency mappings, weighting mechanisms, or other knowledge-based structures and combined with machine learning predictions. Such integration is particularly useful when sufficient historical data are not available or when the relationships between courses and competencies cannot be reliably learned from student behaviour alone. It also provides an opportunity to make recommendations more consistent with educational and pedagogical requirements[9].

A comparison of these approaches indicates that traditional recommendation methods are effective in identifying courses based on learner behaviour or content similarity, while machine learning approaches provide stronger capabilities for discovering patterns and making predictions from learner data. Competency based approaches provide a better representation of learner capabilities, and cognitive skill assessment adds information about the type and level of thinking required for learning. Expert knowledge, in turn, can introduce pedagogical information that may not be available in the data. However, these dimensions are often addressed separately rather than being considered together within a single recommendation process. This observation motivates the development of a framework that combines machine learning with competency information, cognitive skills, and expert knowledge[10].

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Based on the above review, the main research gap lies in the absence of a unified and competency aware course recommendation approach that simultaneously considers the learner's existing competencies, cognitive skill requirements, course characteristics, and expert knowledge. Existing systems can provide personalized recommendations, but their personalization is frequently based on behavioural similarity or historical interactions rather than on the learner's actual capability and expected learning progression. The proposed research addresses this gap by integrating these dimensions into a common machine learning framework with the aim of generating course recommendations that are more closely aligned with individual learner requirements.

3. PROBLEM FORMULATION AND STUDENT COMPETENCY MODELING

3.1 Problem Formulation

The objective of the proposed study is to recommend courses that are appropriate for an individual student based on the student's existing competencies, cognitive skills, and the requirements of available courses.

Let ($S=\{s_1,s_2,\ldots,s_n\}$) represent the set of students and ($C=\{c_1,c_2,\ldots,c_m\}$) represent the available courses. Each student has a competency profile obtained from academic performance and competency related information, while each course is associated with a set of subject competencies and cognitive skill requirements. The recommendation problem can therefore be formulated as the estimation of a relevance score ($R(s_i,c_j)$), which represents the suitability of course (c_j) for student (s_i). The system aims to rank the available courses according to this score and recommend those courses that provide the best alignment between the student's current competency level and the expected requirements of the course.

Unlike conventional recommendation approaches that primarily use previous course selections or learner similarity, the proposed formulation considers the student's academic and competency information as the basis for recommendation. This allows the system to identify not only courses that are likely to be preferred by a student but also courses that are appropriate considering the student's present level of knowledge and skills. The formulation also provides a basis for incorporating expert knowledge into the recommendation process, particularly where the relationship between competencies, cognitive skills, prerequisites, and courses cannot be obtained directly from historical data.

3.2 Subject Competency Representation

Student competency is represented at the subject level so that the system can distinguish between strengths and gaps across different areas of study. Let the competency profile of student (s_i) be represented by a vector ($K_i=[k_{i1},k_{i2},\ldots,k_{ip}]$), where each element ($k_{ir}$) denotes the competency level of the student in a particular subject or competency area. The competency values can be derived from relevant academic and assessment information. Similarly, each course is represented using its expected competency requirements. This representation establishes a direct relationship between what a student currently possesses and what a course is expected to develop or require.

The subject level representation is important because an overall academic score may hide significant differences between individual competency areas. For example, a student may demonstrate strong competency in programming but comparatively lower competency in database concepts. Treating these areas separately allows the recommendation system to identify courses according to the student's actual competency profile rather than relying on a single aggregate measure.

3.3 Cognitive Skill Profiling

In addition to subject competency, the proposed framework considers the cognitive skills associated with the learner and the recommended courses. Cognitive skills represent the level of thinking involved in performing a learning task and may include remembering, understanding, applying, analyzing, evaluating, and creating. A student's cognitive profile can therefore be represented as a vector ($G_i=[g_{i1},g_{i2},\ldots,g_{iq}]$), where each value represents the estimated proficiency of the student at a particular cognitive level.

Course requirements can similarly be represented using a cognitive skill vector. This makes it possible to determine whether the cognitive demands of a course are compatible with the student's current profile. The use of cognitive information is intended to provide an additional dimension to competency matching, since two students with similar subject scores may still differ in their ability to apply, analyze, or evaluate the concepts associated with a particular course[11].

3.4 Cognitive Assessment

The cognitive profile is obtained from assessment information designed to measure different levels of cognitive performance. Questions or assessment activities can be mapped to the corresponding cognitive levels, and the student's performance across these levels is used to estimate the cognitive skill profile. The resulting assessment values provide a more detailed representation of the learner than a single examination score.

For a student (s_i), the assessment results can be represented as ($A_i=[a_{i1},a_{i2},\ldots,a_{iq}]$), where ($a_{it}$) denotes the student's performance at cognitive level (t). These values are subsequently transformed into a common scale before being combined with subject competency information. This process helps reduce the effect of differences in assessment scales and allows competency and cognitive measures to be used together during recommendation[12].

3.5 Normalization

Since academic marks, competency scores, and cognitive assessment results may be expressed using different scales, normalization is performed before constructing the final student representation. For a value (x), min max normalization can be expressed as

$$x'=\frac{x\ x_{\min}}{x_{\max}\ x_{\min}}$$

Where ($x_{\min}$) and ($x_{\max}$) represent the minimum and maximum values within the corresponding assessment or competency scale. The normalized value (x') falls within the range of 0 to 1. Normalization ensures that one component does not disproportionately influence the recommendation model simply because it has a larger numerical range.

3.6 Integrated Student Competency Vector

The subject competency and cognitive skill information are combined to construct an integrated representation of each learner. The integrated student competency vector can be expressed as $V_i=[K_i \; \| \; G_i]$

where (K_i) represents the normalized subject competency vector, (G_i) represents the normalized cognitive skill vector, and (||) denotes vector concatenation. This integrated representation captures both the knowledge and competency related characteristics of the student and the student's cognitive skill profile.

The resulting vector provides the primary learner representation used by the subsequent recommendation model. Course representations can be constructed in a corresponding manner using course competency requirements and cognitive skill requirements. The similarity or compatibility between the student vector and a course requirement vector can then be used as one of the inputs for estimating course suitability. In this way, the proposed framework moves beyond simple preference-based recommendation and establishes a competency-oriented basis for identifying courses that are more closely aligned with an individual student's learning profile[13].

4. PROPOSED COMPETENCY AWARE RECOMMENDATION FRAMEWORK

4.1 Overall System Architecture

The proposed competency aware recommendation framework is designed to generate personalized course recommendations by combining student competency, cognitive skills, course requirements, and expert knowledge. The framework consists of several interconnected stages, beginning with the collection of student academic and assessment information and ending with the ranking of courses according to their suitability for the individual learner. The student information is first processed to construct a competency profile, while course related information is obtained from the expert course skill knowledge base. Both representations are transformed into a common feature space through feature engineering and normalization. The resulting student and course profiles are then compared to determine their level of alignment. Based on this alignment, a recommendation score is calculated for each candidate course, after which the courses are ranked and the most suitable courses are presented to the student.

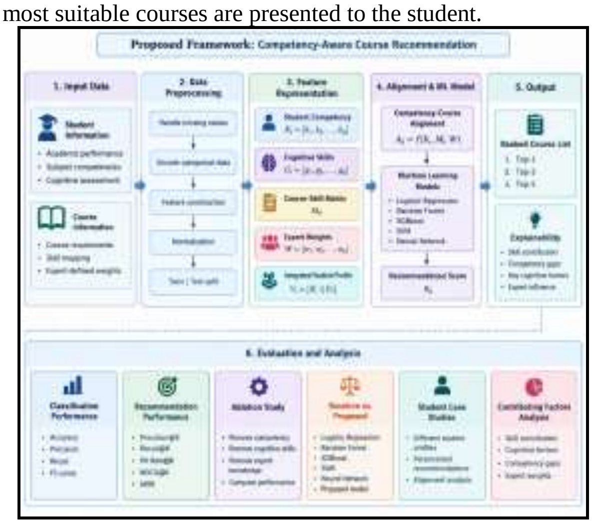

Figure. 1 Overall framework of the proposed competency aware machine learning based personalized course recommendation system

4.2 Student Competency Profile

The student competency profile represents the current learning characteristics of an individual student. It is constructed using subject level competency information together with the cognitive skill profile obtained from the assessment process described in Section III. Academic performance, subject competency, and cognitive assessment results are converted into normalized features so that they can be used consistently by the recommendation model. The profile therefore provides a multidimensional representation of the learner rather than relying on a single academic score. This representation is subsequently used to determine how closely the learner matches the competency and cognitive requirements of each available course.

4.3 Expert Course Skill Knowledge Base

The expert course skill knowledge base contains information about the competencies, prerequisite knowledge, and cognitive skills associated with individual courses. This information is defined with the support of subject experts who understand the learning outcomes and expected requirements of the courses. For each course, the knowledge base can contain a set of required subject competencies and corresponding cognitive skill levels. For example, a course may require a higher level of competency in programming and database concepts and may place greater emphasis on applying and analysing knowledge. Representing these relationships explicitly provides information that may not be available from historical student data alone. The knowledge base therefore acts as a pedagogical component of the proposed recommendation framework[14].

4.4 Feature Engineering and Normalization

The student and course information may initially be available in different formats and numerical ranges. Feature engineering is therefore performed to convert the available information into meaningful features that can be processed by the recommendation model. Subject competency scores, cognitive assessment results, course competency requirements, and cognitive skill requirements are transformed into a consistent representation. Normalization is then applied to minimize the influence of differences in measurement scales. The normalized features allow the framework to compare learner characteristics with course requirements more consistently and provide a suitable input for the subsequent alignment and scoring stages.

4.5 Competency–Course Alignment

The central stage of the proposed framework is the alignment between the student's competency profile and the requirements of a course. Let (V_i) denote the integrated competency vector of student (s_i), and let (Q_j) denote the competency and cognitive requirement vector of course (c_j). The framework compares these two representations to determine the degree to which the student is prepared for, or suitably matched with, the course. A higher alignment value indicates that the student's existing competencies and cognitive skills are more compatible with the requirements of the course.

The alignment process can consider both subject competency and cognitive skill dimensions. Thus, a course is not considered suitable solely because the student has sufficient knowledge of its subject area; the cognitive requirements of the course are also taken into account. This combined alignment helps the framework identify courses that are appropriate for the student's current learning profile.

4.6 Recommendation Score

A recommendation score is calculated for each candidate course based on the competency–course alignment. A general form of the score can be expressed as

[R_{ij}=\alpha S_{ij}+\beta G_{ij}+\gamma E_{ij}] where R_{ij} represents the recommendation score of course c_j for student s_i, S_{ij} represents subject competency alignment, G_{ij} represents cognitive skill alignment, and E_{ij} represents the contribution of expert knowledge. The parameters α, β, and γ determine the relative importance of these components and can be selected or learned according to the experimental design.

This formulation allows the recommendation process to combine data driven learner characteristics with knowledge provided by subject experts. The score can be further extended when additional factors, such as prerequisites, course difficulty, learner preferences, or previous course completion, are included in the proposed implementation[15].

4.7 Course Ranking

After calculating the recommendation score, all eligible courses are arranged in descending order according to their scores. Courses with higher scores indicate stronger compatibility with the student's competency and cognitive profile. Before ranking, courses for which mandatory prerequisites have not been satisfied may be excluded or assigned an appropriate penalty, depending on the implementation of the framework. The ranking process converts the individual alignment scores into an ordered list that can be used directly for personalized course selection.

4.8 Personalized Recommendation

The final stage generates the personalized recommendation list for each student. Instead of presenting all available courses, the framework selects the top ranked courses that demonstrate the strongest alignment with the learner's competency profile and cognitive requirements. The resulting recommendations are intended to support both immediate course selection and progressive skill development. Since the recommendation is based on identifiable competency and cognitive factors, the framework can also provide a more understandable basis for explaining why a particular course has been recommended. This makes the proposed approach potentially useful not only for students but also for teachers and academic advisors involved in planning individualized learning pathways.

5. EXPERT GUIDED COURSE SKILL MODEL AND ML RECOMMENDATION

5.1 Course Skill Matrix

The proposed framework represents the relationship between courses and required skills using a course skill matrix. Let $C=\{c_1,c_2,\ldots,c_m\}$ denote the set of courses and $K=\{k_1,k_2,\ldots,k_p\}$ denote the set of identified competencies or skills. The course skill matrix M is defined as an $m\times p$ matrix, where M_{jr} represents the importance or required level of skill k_r for course c_j. The values in this matrix are determined using course learning outcomes, prerequisite information, assessment requirements, and inputs obtained from subject experts. This representation provides a structured way of describing the skills expected from a student before or during the study of a particular course.

5.2 Expert Defined Skill Weights

Not all skills contribute equally to every course. Therefore, expert defined weights are used to represent the relative importance of individual skills. Subject experts can assign higher weights to skills that are considered essential for understanding a particular course and lower weights to skills that have a supporting role. Let w_r denote the weight assigned to skill k_r. The resulting weight vector is represented as $W=[w_1,w_2,\ldots,w_p]$. These weights introduce domain knowledge into the recommendation process and help prevent the model from treating all competency dimensions as equally important when their actual educational significance may differ.

5.3 Competency–Course Alignment Mathematical Model

Let $V_i=[v_{i1},v_{i2},\ldots,v_{ip}]$ represent the normalized competency profile of student s_i, and let $M_j=[m_{j1},m_{j2},\ldots,m_{jp}]$ represent the required skill profile of course c_j. The weighted competency–course alignment can be expressed as

$$A_{ij}=\frac{\sum_{r=1}^{p}w_r,v_{ir},m_{jr}}{\sum_{r=1}^{p}w_r}$$

where A_{ij} represents the alignment between student s_i and course c_j, v_{ir} represents the student's competency in skill k_r, m_{jr} represents the importance of that skill for course c_j, and w_r represents the expert defined weight.

A higher alignment value indicates stronger compatibility between the student's existing competency and the skill requirements of the course. The formulation can also be extended to include cognitive skill alignment, prerequisite satisfaction, or other learner specific factors when these are available in the experimental dataset.

5.4 ML Recommendation Engine

The competency alignment values and other relevant learner and course features are provided to the machine learning recommendation engine. The purpose of the ML component is to learn the relationship between learner characteristics and suitable course choices from the available training data. Rather than depending entirely on manually defined rules, the model learns patterns from historical student course relationships while retaining the competency and expert knowledge information as important features.

Several supervised machine learning algorithms can be investigated to determine which approach provides the most reliable recommendation performance. The candidate algorithms considered in this study include Logistic Regression, Random Forest, XGBoost, Support Vector Machine (SVM), and Neural Network models. These algorithms provide different modelling capabilities, ranging from relatively interpretable linear relationships to more complex nonlinear relationships between student characteristics and course suitability[16].

5.5 Feature Construction

The feature set used by the recommendation engine is constructed from the student competency profile, cognitive skill profile, course requirements, and expert derived information. Features may include individual subject competencies, cognitive skill levels, competency–course alignment values, expert skill weights, prerequisite indicators, and other relevant course or learner attributes. The purpose of this feature construction stage is to convert the information generated by the earlier stages of the framework into a consistent input representation for machine learning.

Care is taken to avoid unnecessary or highly redundant features because excessive or overlapping information can affect model performance. The final feature vector represents the characteristics that are considered most relevant for determining whether a particular course is appropriate for a given student[17].

5.6 Model Training and Prediction

The constructed dataset is divided into suitable training and testing subsets for developing and evaluating the recommendation models. During training, the selected machine learning algorithms learn the relationship between the input features and the observed course suitability or recommendation outcomes. Model parameters are estimated using the training data, while the unseen test data are used to evaluate the ability of the trained model to make recommendations for students not used during training.

For a new student, the framework first generates the student's competency and cognitive profile and combines it with the feature representation of each eligible course. The trained model then produces a prediction or suitability score for each student course pair. These scores provide the basis for generating the final ranked recommendation list[18].

5.7 Top 1, Top 3 and Top 5 Recommendation

The recommendation engine produces a ranked list of courses according to their predicted suitability scores. To evaluate the usefulness of the recommendation system at different recommendation depths, Top 1, Top 3, and Top 5 recommendation settings are considered. In the Top 1 setting, only the highest ranked course is recommended to the student. In Top 3 and Top 5 settings, the three and five highest ranked courses, respectively, are presented.

Table 1. Competency and Course Feature Representation

Component	Purpose
Subject Competency	Represents student's competency levels
Cognitive Skills	Represents cognitive abilities
Assessment Score	Captures performance in assessments
Course Skill Matrix	Represents skills required by each course
Expert Weights	Represents expert defined importance of skills
Student Profile	Provides an integrated learner representation
Competency Alignment	Measures the match between student competency and course requirements
Recommendation Score	Produces the final suitability score for course ranking

These different recommendation levels provide a more complete evaluation of the proposed framework. Top 1 evaluates whether the system can identify the most ap propriate course directly, whereas Top 3 and Top 5 provide a broader view of whether the relevant course appears among the highest ranked alternatives. The performance of the candidate machine learning models can therefore be compared using these recommendation settings to identify the model that provides the most effective competency aware course recommendations.

6. EXPLAINABLE RECOMMENDATION AND EXPERIMENTAL METHODOLOGY

6.1 Explainable Recommendation Mechanism

An important requirement of a personalized educational recommendation system is that the recommendation should be understandable to the learner and educator. In the proposed framework, the recommendation is therefore not limited to providing a ranked list of courses. The system also identifies the major factors that contribute to the recommendation of a particular course. These factors may include the student's competency in relevant subjects, cognitive skill levels, prerequisite satisfaction, and the importance assigned to specific skills by subject experts. The explanation is generated along with the recommendation score so that the learner can understand the relationship between the existing competency profile and the requirements of the recommended course.

6.2 Skill Contribution Analysis

Skill contribution analysis is used to determine how individual competencies influence the final recommendation. For a given student course pair, the contribution of each skill can be examined using its competency value, course requirement, and expert defined weight. A skill with a higher requirement and stronger expert weight can have a greater influence on the overall alignment score. Similarly, a competency gap can indicate an area in which the student may need additional preparation before undertaking a particular course. This analysis provides a more detailed interpretation of the recommendation and can also help academic advisors understand why a course has received a higher or lower ranking[19].

6.3 Dataset Description

The experimental dataset contains information required to represent both learner characteristics and course requirements. The student related information includes relevant academic performance, subject level competency measures, and cognitive assessment results. Course related information includes course characteristics, re quired competencies, cognitive skill requirements, and expert defined skill weights. The dataset is organized so that each student course relationship can be represented through a common set of features and used by the machine learning models. The final experimental dataset should clearly report the number of students, courses, competency attributes, assessment records, and recommendation instances used in the study.

6.4 Data Preprocessing

Before applying the machine learning algorithms, the collected data undergo preprocessing to improve consistency and suitability for model training. Missing or incomplete values are handled according to the characteristics of the corresponding attribute, while inconsistent records are identified and corrected or excluded where appropriate. Categorical information is converted into a suitable numerical representation, and numerical features are normalized to a common scale. The competency and cognitive assessment information is then combined with course related features to con struct the final input representation. Where applicable, the data are divided into training and testing sets while maintaining an appropriate separation between the information used for model development and final evaluation.

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6.5 Experimental Scenarios

A set of experimental scenarios is defined to examine the contribution of different components of the proposed framework. The first scenario can consider a conventional recommendation approach based primarily on learner or course information. Subsequent scenarios can introduce competency information, cognitive skill information, and expert defined knowledge individually or in combination. The complete proposed framework is then evaluated using all relevant components. Such comparisons help determine whether the addition of competency and cognitive information, together with expert knowledge, produces measurable improvements over simpler recommendation approaches.

6.6 Baseline Models

The proposed approach is compared with suitable baseline models to determine its effectiveness. Baselines may include conventional content based or similarity-based recommendation methods and machine learning models that do not use the complete competency aware representation. The machine learning candidates considered in this study include Logistic Regression, Random Forest, XGBoost, Support Vector Machine, and Neural Network models. Using multiple baseline approaches provides a broader comparison and helps establish whether the improvement obtained by the proposed framework is associated with the integration of competency and expert knowledge rather than the choice of a particular algorithm alone[20].

6.7 Proposed Model

The proposed model combines the integrated student competency representation, cognitive skill profile, course skill requirements, expert defined weights, and ma chine learning prediction. For each student course pair, the framework constructs the required feature representation and calculates the competency–course alignment before generating the recommendation score. The trained machine learning model uses these features to estimate course suitability, after which the candidate courses are ranked according to their predicted scores. The final Top 1, Top 3, and Top 5 recommendations are generated from this ranked list. This experimental setup allows the proposed competency aware approach to be evaluated against the selected base line models under the same data and evaluation conditions.

6.8 Evaluation Metrics

The performance of the recommendation models is evaluated using metrics appropriate for ranked course recommendation. Top 1, Top 3, and Top 5 accuracy can be used to determine whether the relevant course appears within the corresponding recommendation list. Precision@K measures the proportion of recommended courses that are relevant to the learner among the top (K) results, while Recall@K measures the proportion of relevant courses successfully retrieved within the top (K) recommendations. Mean Reciprocal Rank (MRR) can additionally be used to consider the position of the first relevant recommendation in the ranked list. Where the recommendation task is formulated as a classification problem, conventional metrics such as accuracy, precision, recall, and F1 score can also be reported. The same evaluation procedure should be applied to all baseline and proposed models to ensure a fair comparison.

Table 2. Experimental Design and Evaluation Framework

Experimental Aspect	Description
Input Data	Academic performance, competency, cognitive assessment, course requirements and expert knowledge
Preprocessing	Missing value handling, feature construction, encoding and normalization
ML Models	Logistic Regression, Random Forest, XGBoost, SVM and Neural Network
Baseline	Conventional recommendation based on selected learner/course features
Proposed Model	Competency + cognitive skills + expert knowledge + alignment
Recommendation Levels	Top 1, Top 3 and Top 5
Classification Metrics	Accuracy, Precision, Recall and F1 Score
Recommendation Metrics	Precision@K, Recall@K, Hit Rate@K, NDCG@K and MRR
Ablation Study	Removal of competency, cognitive or expert knowledge components
Case Analysis	Comparison of recommendations for different student profiles
Explainability	Identification of competency and cognitive factors influencing recommendations

Overall, the experimental methodology is designed to evaluate not only the predictive performance of the recommendation models but also the contribution of competency information, cognitive skills, and expert knowledge to the final recommendation. The explainability analysis further provides insight into the factors responsible for individual recommendations, thereby supporting the practical use of the frame work in personalized educational decision making.

7. RESULTS, DISCUSSION, ABLATION AND CASE ANALYSIS

7.1 Classification Performance

The classification performance of the considered machine learning models is evaluated using Accuracy, Precision, Recall, and F1 score. These measures provide an overall view of the ability of the models to distinguish between suitable and unsuitable course recommendations. Accuracy measures the proportion of correctly classified instances, while Precision indicates how many of the courses predicted as suitable are actually relevant to the student. Recall measures the ability of the model to identify relevant courses, and F1 score provides a balanced measure of Precision and Recall. The performance of Logistic Regression, Random Forest, XGBoost, SVM, and Neural Network models is compared using the same experimental dataset and preprocessing procedure. The model providing the best balance across these measures is considered the most suitable classification model for the recommendation task.

7.2 Recommendation Performance

Classification performance alone does not fully describe the quality of a course recommendation system because the final objective is to produce a ranked list of suitable courses. Therefore, the recommendation performance is evaluated using Precision@K, Recall@K, Hit Rate@K, NDCG@K, and Mean Reciprocal Rank (MRR). Here, (K) represents the number of courses presented to the student.

Precision@K measures the proportion of relevant courses among the top (K) recommended courses, whereas Recall@K measures how many of the relevant courses are successfully included in the top (K) results. Hit Rate@K determines whether at least one relevant course appears within the top (K) recommendations. NDCG@K considers the position of relevant courses and gives greater importance to relevant courses appearing at higher positions. MRR evaluates the position of the first relevant recommendation and is particularly useful for determining whether the system places an appropriate course near the top of the recommendation list.

The recommendation results are reported for different values of (K), such as Top 1, Top 3, and Top 5. This provides a direct evaluation of the framework's ability to identify an appropriate course as the first recommendation as well as within a small set of alternatives.

7.3 Comparison of Baseline and Proposed Models

The proposed competency aware framework is compared with the selected baseline models under the same experimental conditions. The comparison considers both classification and ranking based recommendation metrics. Baseline models provide a reference point for determining whether the integration of competency information, cognitive skills, and expert knowledge improves recommendation quality.

The comparison should report the performance of each model in a consolidated table containing Accuracy, Precision, Recall, F1 score, Precision@K, Recall@K, Hit Rate@K, NDCG@K, and MRR, where applicable. The results can then be analyzed to determine which model provides the most consistent performance across different evaluation measures. Particular attention should be given to ranking metrics because the primary objective of the proposed system is to place suitable courses at the highest positions in the recommendation list.

7.4 Ablation Study

An ablation study is conducted to understand the contribution of the major components of the proposed framework. The complete model is compared with reduced versions in which selected components are removed. For example, one experimental setting can use only student competency features, another can add cognitive skill information, and a further setting can incorporate expert defined course skill weights. The complete configuration combines all these components. The performance differences between these configurations indicate the individual and combined contribution of the proposed components. If the complete model consistently performs better than the reduced configurations, it provides evidence that competency, cognitive information, and expert knowledge contribute jointly to the recommendation process.

7.5 Student Case Studies

Case based analysis is used to demonstrate how the framework behaves for individual learners. For each selected student, the analysis considers the competency profile, cognitive skill profile, course requirements, alignment score, and final recommendation ranking. Two students with different competency profiles may receive different recommendations even when they have similar academic performance. This demonstrates the importance of considering detailed learner characteristics rather than relying only on aggregate academic scores.

For example, a student with relatively strong programming competency but weaker database competency may receive a different ranking of courses from a student with the opposite competency profile. Similarly, differences in cognitive skills may influence the suitability of courses requiring higher levels of application, analysis, or evaluation. Such cases provide a practical demonstration of the personalization capability of the proposed framework.

7.6 Analysis of Cognitive and Competency Factors

The contribution of individual competency and cognitive factors is further analyzed to understand their influence on the recommendation outcome. The analysis examines which skills contribute most strongly to the competency–course alignment and final recommendation score. Expert defined weights provide an additional basis for interpreting the importance of individual skills.

For a particular student course pair, the contribution of skill (k_r) can be examined using the corresponding student competency value, course requirement, and expert weight. Skills with high relevance to the course and substantial expert weights are expected to have a stronger influence on the alignment score. Conversely, low competency in an important prerequisite skill may reduce the suitability of a course.

This analysis also helps identify competency gaps. When a highly relevant course receives a lower recommendation score because of insufficient competency in one or more required skills, the result can be interpreted as an indication that the student may require prerequisite learning or additional preparation. Thus, the recommendation system can support not only course selection but also the identification of areas for skill development.

7.7 Discussion of Results

The experimental results are interpreted from both predictive and educational perspectives. A model that achieves high classification performance but produces poorly ranked recommendations may not be suitable for practical course recommendation. Therefore, the results from classification metrics and ranking metrics are considered together. The comparison is also used to determine whether the addition of cognitive skills and expert knowledge provides a measurable improvement over approaches based primarily on learner or course features.

The ablation results further indicate which components have the greatest effect on the final recommendation performance. The case studies and factor analysis complement the quantitative evaluation by showing how the framework responds to differences in individual learner profiles. Together, these analyses provide evidence regarding the effectiveness, personalization, and interpretability of the proposed competency aware recommendation framework.

8. CONCLUSION

The proposed framework has certain limitations related to dataset size and diversity, subjectivity in expert defined competency and course skill weights, and the quality of cognitive assessments used to construct student profiles. Since the framework may initially be evaluated using data from limited academic institutions, its generalizability across different institutions and student populations requires further validation. Despite these limitations, the proposed competency aware machine learning frame work integrates student competencies, cognitive skills, course requirements, and expert knowledge to provide personalized and interpretable course recommendations. Unlike conventional approaches that mainly rely on historical preferences or course similarity, the framework considers the alignment between student capabilities and course requirements, supporting more meaningful personalized learning pathways. Future work will explore deep learning and reinforcement learning techniques, adaptive cognitive testing, explainable AI methods, real time student profiling, and continuous recommendation updates. Cross institutional validation using larger and more diverse datasets and large scale deployment will also be considered to evaluate the robustness, scalability, and generalizability of the proposed frame work.

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