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AI-BASED COURSE RECOMMENDATION USING STUDENT SKILLS AND LEARNING HISTORY

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ABSTRACT

Online learning platforms provide courses in programming, data science, communication, business, and many other areas. Although this wide choice is useful, students can find it difficult to decide which course matches their current skills, previous learning, and career goals. This paper proposes an explainable AI-based course recommendation framework that combines a student's skill profile with learning history to rank suitable courses. The framework represents skills and courses using common skill tags, considers course level and prerequisites, and uses a weighted matching score to generate a ranked list. Previous course completion, assessment performance, stated interests, and target skills contribute to the student profile. A rule-based eligibility check is applied before ranking so that a course with unmet prerequisites is not recommended as an immediate next step. The framework is designed to remain understandable: each recommendation includes a short explanation of matched skills, relevant learning history, and any missing prerequisite. A review of recent literature indicates that hybrid recommendation methods are widely used, while cold-start cases, explainability, and evaluation in real learning settings remain important challenges. This paper presents a research design and evaluation plan rather than claiming measured performance. The proposed framework can be implemented and tested using course catalogue data and anonymised learner records, with ranking quality, recommendation coverage, and learner feedback used for evaluation.

KEYWORDS: Artificial Intelligence, Course Recommendation, Student Skills, Learning History, Educational Data Mining, Explainable Recommendation.

1. INTRODUCTION

Digital education has made it possible for students to learn new skills outside the classroom. A learner may choose from hundreds of courses, but the number of options can make course selection confusing. A beginner interested in artificial intelligence, for example, may need Python and basic statistics before starting a machine learning course. A general recommendation based only on popularity may ignore this learning sequence and suggest content that is too easy, too difficult, or unrelated to the learner's goals.

An intelligent course recommendation system can reduce this problem by connecting learner information with course requirements. In this study, artificial intelligence (AI) is used in a practical and interpretable way: the system builds a profile from declared skills and learning history, matches that profile to course metadata, and explains why each course is suggested. The focus is not to replace teachers or academic advisers. Instead, the system offers a useful shortlist that supports student choice.

1.1 Background of the Study

Educational recommender systems use learner information, course descriptions, previous choices, and sometimes assessment results to personalise learning resources. Content-based filtering compares the attributes of a course with a learner's profile, while collaborative filtering uses patterns from learners with similar behaviour. Hybrid approaches combine these sources. Reviews of educational recommendation research identify hybrid methods as common, but also note differences in evaluation methods and limited evidence about pedagogical impact [1, 2].

1.2 Problem Statement

Many students select courses using popularity, advertisements, or informal advice. Such choices may not reflect their existing skills, learning progress, or prerequisite knowledge. Recommendation systems may also struggle when a new student has little interaction history. A practical system is therefore needed that can use both explicit skill information and past learning records, provide recommendations that respect prerequisites, and explain its suggestions in language that students can understand.

1.3 Objectives of the Research

1. Develop a learner profile based on stated skills, interests, career goals, and previous course work.
2. Combine similarity in skills, learning history, interest and course level suitability to develop a course-matching score.
3. Rank courses into a personalized shortlist and run prerequisite checks.

4. To explain each recommendation in layman terms and to identify skill gaps.

5. Specify a plan for evaluation of relevance, coverage and user usefulness of recommendation.

1.4 Research Questions

RQ1: How can student skills and learning history be combined to rank relevant courses?

RQ2: Can prerequisite checks reduce recommendations that are unsuitable for a learner's current level? RQ3: Which evaluation measures can be used to assess recommendation quality without relying on accuracy alone?

1.5 Scope of the Study

The proposed work targets higher-education students and online learning catalogues. It uses structured course metadata and learner-provided or institutionally recorded learning history. It does not diagnose ability, guarantee academic success, or automatically enrol students. The first version is intended as a decision-support prototype; real deployment would require privacy safeguards and validation with students and educators.

2. Literature Review

2.1 Existing Research

Da Silva et al. reviewed educational recommender systems and reported that hybrid approaches were prominent among the studies they examined. Their review also highlighted that evaluations often emphasised recommendation accuracy, while fewer studies examined pedagogical effects [1]. This supports the need to measure more than whether a system predicts a past choice.

Chang et al. developed a personalised hybrid course recommendation system that considered students' interests, abilities, career development, course labels, and past course selections or grades. Their work demonstrates the value of combining course content with learner information [3]. Nguyen et al. proposed a course recommendation model based on learning outcomes and analysed academic records from 510 students, comparing prediction approaches for course selection [4]. These studies show that learning history can be a useful signal, although a model trained on one institution's records may not transfer directly to another context.

Algarni and Sheldon reviewed course-selection recommendation systems and identified continuing challenges such as the large and changing course space and the cold-start problem for new students [2]. Narimani and Barberà examined course features and learner profiling, emphasising the importance of representing both courses and learners in a meaningful way

[5]. More recent work on academic course planning also combines multiple educational data sources to support recommendations and performance prediction [6].

Table 1. Comparison of Selected Research on Educational Recommendation.

Study	Main Approach	Contribution	Issue Relevant to This Study
Da Silva et al. [1]	Systematic review	Summarises methods and evaluation practices	Need to evaluate pedagogical usefulness as well as ranking quality
Algarni and Sheldon [2]	Review of course-selection systems	Discusses methods and cold-start challenges	New learners may have little interaction data
Chang et al. [3]	Personalised hybrid course	Combines interests, abilities,	A recommendation should
	recommendation	course labels, and past choices	also show why a course fits
Nguyen et al. [4]	Learning-outcome-based course recommendation	Uses academic records and compares prediction methods	Institution-specific records may limit transferability
Narimani and Barberà [5]	Review of course features and learner profiling	Highlights learner and course representation	Profile features need to be clear and consistently defined

2.2 Comparison of Existing Methods

Content-based filtering is useful when course descriptions and learner skills can be represented with common tags. It can recommend a course to a new student if the student provides a basic profile, but it depends on the quality of course metadata. Collaborative filtering can identify useful patterns among similar learners, but it performs poorly when interaction records are sparse. Hybrid methods can balance these limitations, though they require careful design and may be harder to explain. For this reason, the proposed framework uses content-based skill matching as its main component and treats learning history as an additional signal rather than making past enrolment the only basis for a recommendation.

Table 2. Strengths and Limitations of Recommendation Approaches.

Approach	Strength	Limitation	Proposed Use
Content-based	Works with course tags and a new learner profile	Depends on complete, accurate metadata	Core skill-to-course matching
Collaborative filtering	Learns from similar learners' choices	Cold-start and sparse-history problems	Optional extension when sufficient records exist
Hybrid recommendation	Combines multiple information sources	Weights and explanations need careful design	Combine skills, interests, and learning history
Prerequisite rules	Prevents immediate suggestions that require missing foundations	Rules must be maintained by course experts	Eligibility check before final ranking

2.3 Research Gap

The literature indicates that combining learner profiles with course information is established, so the contribution of this paper is not the claim that course recommendation is new. The proposed gap is narrower and practical: a lightweight framework that joins declared skills and learning history with prerequisite-aware ranking and student-readable explanations, while defining an evaluation plan suitable for a small academic prototype. The framework also keeps a transparent fallback for new learners who have no prior course history.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study follows a design-oriented research approach. A recommendation framework is specified, its inputs and scoring logic are defined, and an evaluation protocol is proposed. The present paper does not report a completed user trial or measured model accuracy. Those results must be obtained after implementation using an approved dataset and a documented experiment.

3.2 Data Collection

Two data sources are planned. The course catalogue contains course title, description, skill tags, difficulty level, prerequisites, estimated duration, and learning outcomes. The learner profile contains self-reported skills, interests, career goals, completed courses, assessment results where available, and course completion status. Data should be collected with appropriate permission. Names, email addresses, and other direct identifiers are not needed for ranking and should be removed before analysis.

3.3 Dataset

For an initial prototype, a small manually verified course catalogue can be prepared from publicly available course descriptions. Learner records should be anonymised and obtained with institutional approval or from a suitable public educational dataset. The final paper should state the actual source, number of learners and courses, date of collection, missing-value treatment, and train/test split after the dataset has been selected. No dataset size is invented in this proposal.

Table 3. Data Fields Planned for the Proposed Framework.

Data Group	Example Fields	Purpose
Student skills	Python: beginner; SQL: intermediate; communication: basic	Represent current capability
Learning history	Course completed, score band, completion status, timestamp	Estimate progress and reinforce demonstrated learning
Student goals	Target role, topic interests, preferred level	Personalise recommendations
Course metadata	Skill tags, level, duration, prerequisites, outcomes	Describe course requirements
Feedback	Clicked, saved, started, completed, helpful/not helpful	Support evaluation and future updates

3.4 Tools and Technologies

A prototype can be implemented in Python using pandas for data preparation, scikit-learn for text vectorisation and similarity calculations, and a simple web interface such as Streamlit for demonstration. A relational database such as MySQL or SQLite can store course metadata and anonymised interactions. These are proposed tools, not a claim that the system has already been deployed. The implementation environment and library versions should be recorded to make the experiment reproducible.

3.5 Proposed Methodology

First, course descriptions and skill tags are cleaned and standardised. Synonyms such as “machine learning” and “ML” are mapped to a common vocabulary where appropriate. Second, the student profile is built from declared skills and learning history. Completed courses and assessment outcomes can increase confidence in a skill, while an unfinished course should not automatically be treated as mastery. Third, each course is checked against its prerequisite rules. Courses with unmet mandatory prerequisites are either filtered out or shown as a later learning goal with the missing prerequisite clearly stated.

For eligible courses, a weighted score is calculated from skill match, interest match, level suitability, and learning-history relevance. The weights are configurable and should be selected using validation data or stakeholder input, not chosen to make results appear better. The highest-scoring courses are returned with short explanations. Finally, user feedback can be collected to assess usefulness and support future updates.

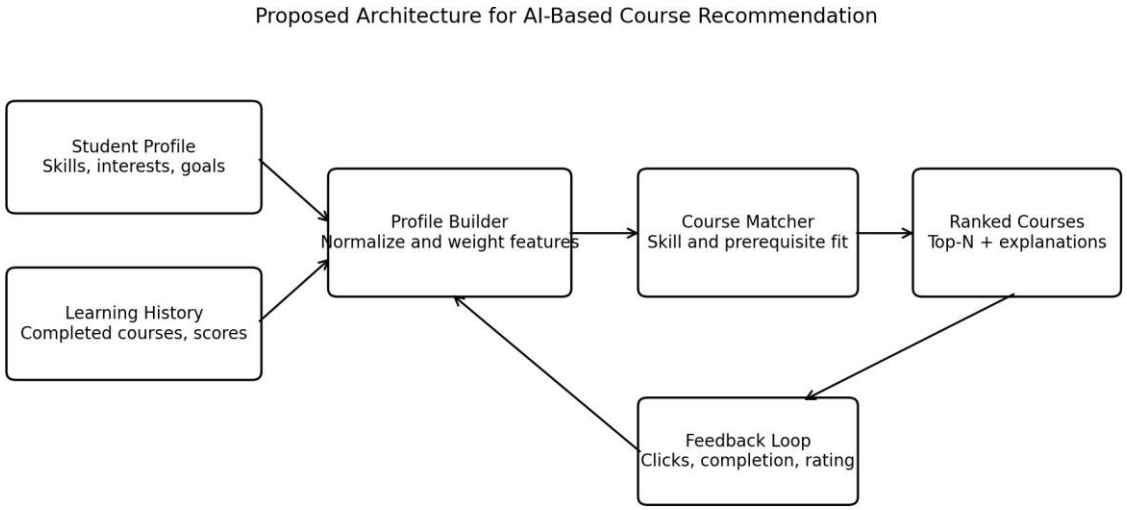

Figure 1. Proposed Architecture for AI-Based Course Recommendation.

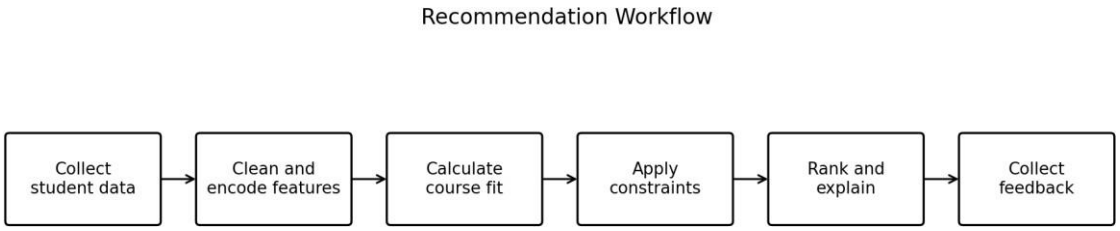

Figure 2. Workflow from Learner Data to Ranked Course Recommendations.

3.6 Algorithms and Ranking Score

A simple and interpretable scoring function is proposed. Let S be skill match, I be interest match, L be level suitability, and H be learning-history relevance, each normalised to a value between 0 and 1. The recommendation score is:

$$\text{Score(course)} = 0.45S + 0.20I + 0.20L + 0.15H$$

The weights above are initial design values only and must be tuned or validated experimentally. Skill match receives the largest initial weight because the paper focuses on matching current skills to course requirements. For a new learner without history, the remaining weights can be renormalised across available features. A prerequisite rule is applied separately so that a high score cannot override a mandatory requirement. Skill similarity may be calculated using weighted tag overlap or cosine similarity between text vectors. The prototype should compare at least a popularity baseline, content-based ranking, and the proposed combined score.

3.7 System Architecture

The architecture has six functional stages: learner input, course and history data preparation, profile construction, course matching, prerequisite filtering and ranking, and explanation with feedback. The profile builder creates a compact skill representation rather than using

unnecessary personal data. The matching module compares that profile with the course catalogue. The explanation module identifies the strongest matching skills, relevant completed learning, and any missing prerequisite. Feedback is stored separately and used only for evaluation or later model updates.

4. Implementation and Experimental Setup

The implementation should begin with a course table and an anonymised learner table. A preprocessing script standardises skill labels, checks missing fields, and converts categorical levels into a consistent scale. A recommendation function then calculates feature scores for every course, applies prerequisite constraints, sorts the eligible courses, and returns the top five or top ten results. The interface should display course title, level, duration, matched skills, and a plain-language explanation. Students should be able to mark a suggestion as relevant or not relevant.

For a fair comparison, all recommendation methods should use the same catalogue and evaluation split. If historical enrolments are available, earlier interactions should be used to build profiles and later interactions should be held out for testing; random splitting may leak future information into training. If a public dataset is unavailable, a small expert-reviewed pilot can assess explanation clarity, but it should not be presented as evidence of general predictive performance.

5. RESULTS AND DISCUSSION

5.1 Results Status

No experimental dataset or implementation output was supplied for this paper. Therefore, measured accuracy, precision, recall, or user satisfaction cannot be reported honestly at this stage. The contribution presented here is a clearly specified framework and a reproducible plan for evaluating it. The following table lists the measures to report after experiments are completed; its entries are evaluation requirements, not achieved results.

Table 4. Evaluation Plan and Measures to Report.

Measure	What It Shows	How It Will Be Used
Precision@K	Share of top-K recommendations judged relevant	Checks how useful the displayed shortlist is
Recall@K	Share of relevant held-out courses found in top K	Checks whether relevant options are missed
NDCG@K	Rewards relevant courses placed higher in the list	Measures ranking quality
Catalog coverage	Share of catalogue items recommended to at least one learner	Checks whether recommendations are too narrow
Cold-start coverage	Ability to return suitable results for learners with little history	Tests the profile-based fallback
User rating	Student judgement of relevance and explanation clarity	Assesses practical usefulness

5.2 DISCUSSION

The main design choice is to use skills and course metadata as the starting point, with learning history as supporting evidence. This makes the framework usable for students who are new to a platform and have not generated enough interactions for collaborative filtering. Prerequisite checks can make the recommendations more educationally sensible, while explanations may help students understand both why a course fits and what they should learn first. However, these benefits are design expectations and need to be confirmed through evaluation.

Several risks must be considered. Self-reported skills may be inaccurate, course tags may be incomplete, and assessment scores may not measure the full range of a learner's ability. Historical enrolment data may also reflect unequal access rather than genuine interest. To reduce these risks, the system should allow students to correct their profiles, avoid using sensitive attributes for ranking, explain recommendations, and offer alternatives rather than treating the score as a final decision. Educators should review prerequisite rules and course labels before the system is used at scale.

6. CONCLUSION

This paper proposed an AI-based course recommendation framework that combines student skills, interests, learning history, and course prerequisites. A transparent weighted score is used to rank eligible courses, and each suggestion is accompanied by an explanation of matched skills and possible learning gaps. The design responds to practical issues identified in educational recommendation literature, particularly cold-start learners and the need for broader evaluation. Since no experiments have yet been completed, no performance improvement is claimed. The next step is to implement the prototype, obtain an appropriate anonymised dataset, compare it with baseline methods, and report ranking and user-study results.

7. Future Scope

Future work can test the framework with a larger and more diverse course catalogue, compare different feature weights, and study whether recommendations improve course completion or learner confidence over time. Natural-language processing could improve skill extraction from course descriptions, while knowledge graphs could represent prerequisite relationships more richly. Additional work should examine fairness across learner groups, privacy-preserving analytics, changing course content, and explanations that are understandable to

students with different levels of technical knowledge.

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