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Agentic AI-Based Student Career Readiness Platform

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Abstract- SkillPath AI is an Agentic AI-based student career readiness platform proposed to bridge the gap between academic learning and industry requirements. The platform aims to provide personalized career guidance by analyzing students' skills, career objectives, and learning requirements to identify skill gaps and recommend relevant technical skills. The proposed system follows a modular architecture consisting of a React-based frontend, Java Spring Boot backend, and Python FastAPI-based AI service. PostgreSQL with the pgvector extension is used for structured data management and embedding-based semantic similarity search. The currently implemented Skill Agent focuses on retrieving students' target career roles and generating relevant skill recommendations through semantic search and AI-service integration. It uses sentence-transformer-based embeddings to represent skills in a vector space and identify relevant skills based on career requirements. A locally deployed Large Language Model (LLM) through Ollama provides the foundation for AI-assisted interactions. The overall platform is designed to extend this functionality through additional intelligent agents for adaptive assessment, personalized learning, and career recommendations. This modular approach aims to establish an integrated and student-centric framework for improving career readiness through intelligent skill analysis and personalized recommendations.

I. INTRODUCTION

Artificial Intelligence (AI) is increasingly transforming the education sector by supporting personalized learning, student performance analysis, and career guidance. Traditional educational platforms primarily provide predefined learning materials, while conventional career guidance systems often generate general recommendations based on student profiles. These approaches may not sufficiently address individual learning requirements, existing skill gaps, and continuously evolving industry demands. Recent advancements in Agentic Artificial Intelligence (Agentic AI) and Large Language Models (LLMs) provide opportunities to develop intelligent systems capable of reasoning, planning, interacting with external tools, and supporting personalized decision-making [1], [2].

Personalized learning systems aim to adapt educational recommendations according to students' knowledge levels, learning progress, and individual requirements. Artificial intelligence and machine learning techniques can support the identification of knowledge gaps, assessment of student competencies, and organization of relevant learning resources into structured learning paths. Research on knowledge tracing and personalized learning path generation demonstrates the importance of considering students' existing knowledge and learning characteristics when providing educational recommendations [3], [4].

In addition to academic learning, students require industry-relevant technical skills and appropriate career guidance to improve their employment opportunities. Identifying suitable career roles requires understanding the relationships between students' existing competencies, required job skills, and industry expectations. Semantic search and vector-based retrieval techniques provide an approach for identifying relevant information based on contextual similarity rather than relying exclusively on exact keyword matching [5]. Similarly, machine learning and knowledge graph-based recommendation approaches have been explored for matching candidate profiles with suitable career opportunities [3], [4], [10].

To address these challenges, SkillPath AI – Agentic AI-Based Student Career Readiness Platform is proposed as an integrated solution for personalized skill development and career preparation. The proposed platform is designed around a modular architecture consisting of a React-based frontend, Java Spring Boot backend, and Python FastAPI-based AI service. PostgreSQL with the pgvector extension is used for

structured data management and embedding-based semantic similarity search. Redis and Neo4j are included as supporting technologies in the broader system architecture for caching and knowledge relationship representation. The architecture also considers the integration of a locally hosted Large Language Model (LLM) through Ollama to support future AI-assisted interactions and intelligent workflows.

The current implementation primarily focuses on the Skill Agent, which retrieves the authenticated student's selected target career role and generates relevant skill recommendations using semantic search over skill embeddings stored in PostgreSQL with pgvector. The Spring Boot backend communicates with the Python FastAPI AI service to process skill recommendation requests and return relevant results to the frontend. This component establishes the foundation for the broader platform, which is intended to be extended with additional intelligent agents for adaptive assessments, personalized learning recommendations, career guidance, and job recommendations.

The proposed platform aims to bridge the gap between academic learning and industry skill requirements by providing a unified and student-centric approach to career readiness. Through the integration of semantic skill matching and specialized AI capabilities, the system is intended to support students in understanding their career requirements and identifying relevant skills for their professional development. Further development and evaluation will focus on adaptive learning, assessment-driven skill progression, recommendation effectiveness, data privacy, system scalability, and alignment with evolving industry requirements.

II. LITERATURE REVIEW

Recent advancements in Agentic Artificial Intelligence (Agentic AI) and Large Language Models (LLMs) have introduced new possibilities for developing intelligent systems. Lee and Kim [6] discussed LLM agent architectures involving reasoning, memory, planning, and tool utilization. Similarly, Singh et al. [11] explored agentic workflows based on planning, reflection, tool usage, and multi-agent collaboration. These studies provide a foundation for developing modular AI-based applications.

Personalized learning has been explored through knowledge tracing and recommendation techniques. Wei et al. [8] proposed a personalized learning path generation strategy based on students' knowledge levels and learning requirements. Ngo et al. [5] combined Knowledge Graph Embedding, Collaborative Filtering, and Sequence Mining to recommend personalized learning resources. Hang et al. [9] explored the use of Large Language Models for automatic multiple-choice question generation, demonstrating the potential of AI-assisted assessment in personalized learning. Li et al. [13] and Vaisakh et al. [1] investigated knowledge tracing and skill assessment techniques for monitoring student learning progress.

Semantic search and vector-based retrieval are important for generating relevant recommendations. Shan [12] discussed vector stores and their role in embedding-based semantic search and Retrieval-Augmented Generation. In career recommendation, Bairi and Prasad [3] explored machine learning-based career prediction, while Upadhyay et al. [10] and Seetaworn et al. [2] investigated knowledge graph-based job and internship recommendations.

The reviewed studies provide useful approaches for AI agents, personalized learning, skill assessment, semantic retrieval, and career recommendation. However, integrating these capabilities into a unified student career readiness platform remains an important development area. SkillPath AI addresses this through its currently implemented Skill Agent, which uses semantic search and skill embeddings to recommend relevant skills based on students' selected career roles. The broader platform is designed for future extension with adaptive assessment, personalized learning, and career guidance capabilities.

III. KEY FINDINGS

The reviewed studies highlight the importance of Agentic AI, personalized learning, semantic search, and intelligent recommendation techniques in developing student career readiness platforms. Lee and Kim [6] and Singh et al. [11] demonstrate how LLM agents, planning, memory, and tool utilization can support modular and intelligent system architectures.

Research on career recommendation by Bairi and Prasad [3], Upadhyay et al. [10], and Seetaworn et al. [2] highlights the importance of matching students' competencies with career

requirements using machine learning and knowledge graph-based approaches. These techniques can help identify relevant skills and establish connections between academic knowledge and industry expectations.

Studies by Wei et al. [8] and Ngo et al. [5] demonstrate the importance of personalized learning paths based on learner characteristics, knowledge relationships, and learning patterns. Similarly, knowledge tracing approaches [1], [13], [14] provide foundations for evaluating student knowledge and monitoring skill development. Shan [12] highlights the role of vector stores in enabling embedding-based semantic search and relevant information retrieval.

Based on these findings, integrating semantic skill recommendations with personalized career guidance provides an important direction for student career readiness. SkillPath AI currently implements the Skill Agent, which uses sentence-transformer embeddings and PostgreSQL with pgvector to recommend relevant skills according to students' selected career roles. The broader platform is designed for future extension through adaptive assessment, personalized learning, and additional intelligent agents.

IV. RESULT AND DISCUSSION

The reviewed studies provide a foundation for developing intelligent student career readiness systems. Lee and Kim [6] and Singh et al. [11] highlight the importance of LLM agent architectures, planning, memory, and tool utilization in developing modular AI applications.

Research by Li et al. [13], Gu et al. [14], and Vaisakh et al. [1] demonstrates how knowledge tracing and skill assessment techniques can support the evaluation of student knowledge and learning progress. Similarly, Wei et al. [8] and Ngo et al. [5] explore personalized learning recommendations based on learner characteristics, knowledge levels, and relationships between learning resources.

Shan [12] explains the importance of vector stores and embedding-based retrieval for semantic search and context-aware recommendations. These techniques are relevant to identifying skills based on contextual similarity rather than exact keyword matching.

Based on these findings, SkillPath AI implements a Skill Agent that uses sentence-transformer embeddings and PostgreSQL with pgvector to generate skill recommendations according to students' selected career roles. The broader platform is designed for future integration of adaptive assessments, personalized learning, and career guidance. Further evaluation will be required to measure recommendation relevance, system reliability, and the effectiveness of the proposed platform in supporting student career readiness.

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V. ALGORITHMS AND MATHEMATICAL FORMULATION

1. Sentence Transformer-Based Embedding Generation

SkillPath AI uses the pre-trained all-MiniLM-L6-v2 model to convert career-related queries and skill descriptions into numerical embeddings of 384 dimensions.

Mathematical formulation:

$$H = \text{Transformer}_\theta(t)$$

Mean pooling generates the sentence embedding:

$$E(t) = \frac{\sum_{j=1}^{T} m_j h_j}{\sum_{j=1}^{T} m_j}$$

Where t represents input text, \(h_j\) represents token embeddings, \(m_j\) is the attention mask, and \(E(t)\) is the final sentence embedding.

Output:

$$E(t) \in \mathbb{R}^{384}$$

2. Cosine Similarity

Cosine Similarity measures the semantic similarity between a student's career-related query embedding and stored skill embeddings. It calculates the similarity based on the angle between two vectors.

Mathematical formulation:

$$\text{CosSim}(A, B) = \frac{A \cdot B}{\|A\| \times \|B\|}$$

Where:

- A = Student query embedding.
- B = Skill embedding.
- A.B = Dot product of vectors.
- ||A|| , ||B ||= Vector magnitudes.

Cosine Distance:

$$d(A, B) = 1 - \text{CosSim}(A, B)$$

A higher cosine similarity indicates greater semantic similarity, while a lower cosine distance indicates a closer match.

3. Vector-Based Retrieval Using PostgreSQL and pgvector

SkillPath AI uses PostgreSQL with the pgvector extension to store and retrieve skill embeddings. The system compares the student's query embedding with stored skill vectors to identify relevant technical skills.

Mathematical formulation:

$$\boxed{d_i = 1 - \frac{Q \cdot S_i}{\|Q\|\|S_i\|}}$$

The retrieved skills are ranked in ascending order of distance.

4. Top-K Skill Recommendation Algorithm

SkillPath AI uses the Top-K retrieval technique to select the most relevant skills from the available skill database based on their semantic similarity scores.

Mathematical formulation:

$$\boxed{R_K(Q) = \arg\min_{R \subseteq S,\, |R|=K} \sum_{S_i \in R} d\,(Q, S_i)}$$

The system selects the K skills having the smallest vector distances.

5. Rule-Based Skill Prioritization

SkillPath AI uses deterministic rule-based logic to prioritize skill gaps based on students' existing skill information, learning history, and predefined thresholds.

Mathematical formulation:

$$\boxed{P_i = H(X_i; \Theta)}$$

The system applies predefined conditions to determine skill priorities without requiring machine learning model training.

6. Career Role-Based Skill Recommendation

SkillPath AI uses the student's selected target career role to generate relevant technical skill recommendations through semantic search.

Mathematical formulation:

$$q_u = g(R_u)$$

$$E_u = f_\theta(q_u)$$

$$\boxed{\text{Recommendations}(u) = \text{TopK}_{s_i \in S} d(E_u, E(s_i))}$$

The system retrieves the target career role, generates its embedding, and identifies relevant skills using vector similarity retrieval.

VI. FUTURE SCOPE

SkillPath AI provides a foundation for developing an integrated student career readiness platform. The current implementation focuses on the Skill Agent, which generates career-oriented skill recommendations using semantic search. Several enhancements can be introduced in future versions to extend the platform's capabilities.

Future development may include additional intelligent agents for adaptive assessment, personalized learning, career guidance, and job recommendations. Knowledge Tracing techniques could be integrated to evaluate students' knowledge levels, analyze assessment results, and monitor skill development. These insights could help generate adaptive learning roadmaps based on individual competencies and learning progress.

The platform could also incorporate advanced Agentic AI capabilities, including task planning, memory management, tool utilization, and coordination between specialized agents. Integration with external job portals and industry databases could provide updated information about employment opportunities, internships, and in-demand technical skills. Additional features such as resume analysis, mock interviews, coding assessments, and project-based evaluations could further improve career preparation.

Explainable AI techniques could enhance recommendation transparency by providing reasons behind suggested skills and career opportunities. Advanced dashboards could visualize student progress, skill development, and career readiness. Future improvements should also focus on data privacy, security, scalability, recommendation reliability, and evaluation using real-world student interactions.

These enhancements aim to transform SkillPath AI into a comprehensive and adaptive student career readiness platform that connects academic learning, technical skill development, and evolving industry requirements.

VII. CONCLUSION

This research presents SkillPath AI, an Agentic AI-based student career readiness platform designed to bridge the gap between academic learning and industry skill requirements. The reviewed studies highlight the potential of intelligent agents, semantic search, personalized recommendations, and knowledge-based techniques in supporting student skill development and career preparation.

The current implementation focuses on the Skill Agent, which retrieves students' selected career roles and generates relevant technical skill recommendations using sentence-transformer-based embeddings and semantic similarity search. The system utilizes a React-based frontend, Java Spring Boot backend, and Python FastAPI AI service, with PostgreSQL and pgvector supporting structured data management and vector-based retrieval. This implementation establishes the foundation for the broader SkillPath AI architecture.

The proposed platform aims to extend these capabilities through additional intelligent agents for adaptive assessment, personalized learning, and career guidance. Its objective is to help students identify relevant skill requirements and progressively prepare for their selected career roles.

Although the current implementation establishes the foundation for semantic skill recommendations, further development and experimental evaluation are required to assess recommendation relevance, system performance, reliability, and practical effectiveness. Overall, SkillPath AI represents an approach towards connecting student competencies with industry-oriented skill requirements through intelligent and personalized career guidance.

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