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AI-Powered Personalized Learning and Career Enhancement Platform

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Abstract

Choosing a suitable career has become increasing obstacle for students in higher secondary and undergraduate programs. Many students find it difficult to identify career paths that align with their interests, psychological traits, and skill levels. Traditional career counselling app methods typically depend on static questionnaires and general recommendations, which often fail to address individual uniqueness. This study proposes an AI-powered personalized learning and career enhancement platform that combines psychological assessment, career recommendation, and adaptive course generation. The system leverages Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) to provide intelligent and context-aware guidance. Users are tested through dynamically generated psychological questions designed to identify personality traits and career inclinations across multiple dimensions. Based on the psychological profile and skill-level assessment, the system recommends suitable career paths and generates a customized learning roadmap. Developed using Python and Django, the platform ensures continuous interaction between reasoning models and knowledge retrieval mechanisms. The proposed solution Aims to improve career clarity and learning efficiency through end-to-end personalization.

Keywords: *Personalized Learning, Career Recommendation, Psychological Assessment, Large Language Models, Retrieval-Augmented Generation Acceptable career options that match with their Interests, behavioral features, and skill levels. Traditional career advising systems rely on static questionnaires and broad recommendations, which often fail to reflect individual differences. This study presents an AI-powered personalized learning and career advancement platform that incorporates psychometric analysis, career advice, and adaptive learning generation. The system leverages Large Language Models (LLMs) to conduct dynamic psychological examinations using indirect and adaptive questioning techniques. Career Recommendation, Psychological Assessment, LLM, RAG.*

1. Introduction

Career guidance systems have evolved significantly, moving from traditional manual counselling methods to computer-assisted and AI-driven approach. Early systems were primarily rule-based, where predefined mappings connected with aptitude scores and career options. Although helpful, these systems lacked flexibility and personalization. Recent advancements introduced machine learning techniques such as decision trees, clustering, and recommender systems for career prediction. However, these models often depend on structured datasets and struggle to capture qualitative psychological traits. With the emergence of Large Language Models (LLMs), research has shifted toward conversational career guidance and intelligent tutoring systems. Retrieval-Augmented Generation (RAG) enhances generative AI models by combining information retrieval with content generation, thereby reducing hallucination and improving accuracy. While RAG has been successfully applied in educational systems, limited research integrates psychological trait analysis with RAG for complete career and learning customization. Rapid technological advancements with changing industry demands have made career planning more complex. Academic qualifications alone are no longer sufficient for long-term growth. Continuous skill development and adaptability are important. This research proposes

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an integrated AI-driven framework that integrates psychological assessment, career intelligence, and personalized course generation

1.1.Related Work

Career guidance systems have evolved from manual counselling methods to computer-assisted and AI-driven solutions. Early systems primarily relied on rule-based expert systems, where predefined rules mapped aptitude scores to career options. While effective to an extent, these systems lacked flexibility and personalization. Recent studies have explored machine learning techniques such as decision trees, clustering, and recommender systems for career prediction. Some approaches utilize academic performance and interest surveys to suggest career paths. However, these models often depend on structured datasets and struggle to incorporate qualitative psychological traits. With the emergence of LLMs, research has shifted toward conversational career guidance and intelligent tutoring systems. Retrieval-Augmented Generation has been introduced to mitigate hallucination issues in LLMs by combining retrieval mechanisms with generative models. Although RAG has been successfully applied in education for question answering and content generation, limited research integrates RAG with psychological trait analysis for end-to-end career and learning personalization. This work addresses that gap by combining psychological assessment, career recommendation, and RAG-based personalized course generation within a unified framework. Several studies have examined individualized adaptive learning utilizing machine learning and data-driven methodologies. Prior research mostly focuses on learning style identification and material adaptation. Machine learning models such as decision trees, neural networks, and clustering algorithms have been utilized to assess learner behaviour. However, most systems lack holistic profiling and real-time adaptation. Recent AI-driven tutoring systems employ NLP and recommender systems, although verified content development and integrated career coaching remain limited. These limitations underscore the need for a single platform combining adaptive learning with career-oriented suggestions

2. Proposed Method

The proposed platform follows a modular and adaptive architecture to assure end-to-end personalization. The methodology is structured as interconnected stages where each stage feeds into the next. The system is developed using Python and Django and integrates a Large Language Model (LLM) with Retrieval-Augmented Generation (RAG) to produce accurate and context-aware outputs. Major modules include User Authentication, Adaptive Psychometric Assessment, Personality Trait Analysis, Career Recommendation Engine, Skill-Level Assessment, RAG-Based Course Generator, and Learning Analytics. The adaptive psychometric assessment dynamically generates 10–15 indirect questions to reduce bias and evaluate traits such as creativity, analytical thinking, leadership, emotional intelligence, and adaptability. Responses are semantically analysed to determine normalized trait scores. The career recommendation engine uses reasoning based matching between personality profiles and suitable career domains. After selecting a career, users need to take a skill-level assessment and are classified as Beginner, Intermediate, or Advanced. This classification analyses the depth and structure of the personalized learning roadmap. The RAG pipeline retrieves relevant domain knowledge, converts documents into embeddings, stores them in a vector database, and injects retrieved knowledge into LLM prompts before content generation. This ensures accurate, personalized, and domain-aligned course structures[1].

3. Method A Framework For Learning Based On Prompts And Knowledge

The suggested AI-powered personalized learning and career advancement platform does not use traditional data preparation or model training based on datasets. Instead, the system leverages a pertained Large Language Model (LLM), QWEN (Queen Bit) 5.0, which is customized for domain

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specific reasoning utilizing prompt-based fine tuning and structured knowledge integration. This approach eliminates the need on huge, labelled datasets while providing dynamic personalization through intelligent prompt design and Retrieval Augmented Generation (RAG).

3.1.Use Of Pre-Trained Large Language Model

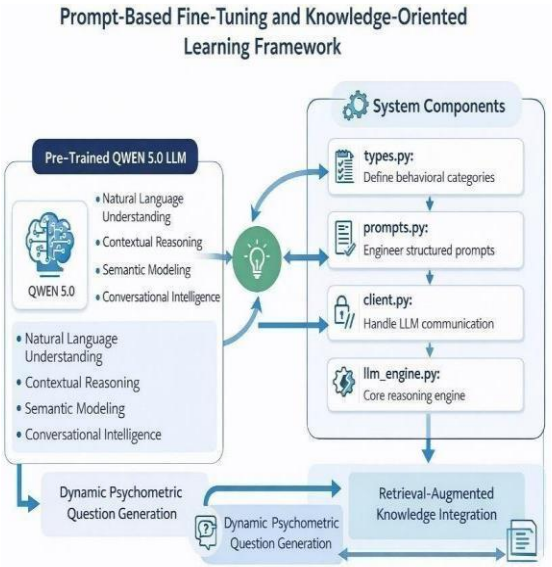

Figure 1: QWEN

The foundation of the system is a pre-trained transformer based LLM, QWEN 5.0, which already possesses:

- Natural language understanding capabilities.
- Reasoning and contextual inference abilities Semantic relationship modelling.

Conversational intelligence Rather than retraining or altering internal model parameters, the system exploits the in-context learning capacity of the LLM.
This strategy ensures:

- Reduced computational cost.
- Faster deployment.
- Improved stability.
- Avoidance of over fitting risks

3.2.Prompt-Based Fine-Tuning Strategy

Instead of dataset-driven training, the suggested approach utilizes prompt-based fine-tuning, which regulates model behavior using specified instructions.
This fine-tuning process is implemented using:

- types.py
- prompts.py

These files define how the LLM should think, respond, assess, and classify users.

3.3.Role Of Types.Py

The types.py module defines structured behavioral categories utilized across the system.

Examples include:

- Creativity-oriented responses
- Analytical thinking patterns
- Logical reasoning behavior
- Emotional intelligence indicators
- Leadership tendencies

Each category functions as a semantic restriction, leading the LLM toward consistent psychological interpretation.

Instead of learning from datasets, the model learns through explicit behavioral definitions encoded into prompts.

3.4.Role Of Prompts.Py

The prompts.py file contains carefully engineered prompts that define:

- Question generation style.
- Psychological tone (indirect, introspective, therapist-like)
- Answer interpretation format.
- Trait extraction logic
- Career reasoning instructions These prompts ensure that:
- The LLM does not produce random questions.
- Each question serves a psychological objective.
- Outputs remain constant among users this mechanism functions as a soft fine-tuning layer, aligning the general-purpose LLM

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with the domain of psychology-based learning customization.

3.5.LlM Interaction Architecture

Communication with the LLM is handled by a specific abstraction layer developed in: Implemented in:

- client.py
- llm_engine.py

3.6.Client.Py

- The client.py module manages: Secure LLM API communication
- Request formatting.
- Response handling
- Error recovery techniques
- This layer ensures segregation between application logic and model inference.

3.7.Llm_Engine.Py

The llm_engine.py acts as the main reasoning engine that:

- Injects prompts dynamically.
- Appends user context.
- Integrates recovered knowledge (RAG)
- Enforces reaction structure.

This architecture enables the machine to replicate human-like reasoning instead of static prediction.

3.8.Motivation For Rag Integration

Although huge language models hold wide knowledge, they may:

- Generate generic responses.
- Lack domain specificity.
- Produce hallucinated content to circumvent these restrictions, RAG adds external verified knowledge sources into the generation process [3].

3.9.Knowledge Base Construction

The system stores organized knowledge files saved in JSON format:

- course_content.json
- psychology_docs. Json

These documents contain:

- Learning ideas
- Career-specific skill frameworks
- Psychological reference knowledge
- Educational domain explanations

3.10. Knowledge Processing Pipeline

The RAG pipeline includes the following components:

- loader.py – loads domain documents.
- chunker.py - separates information into semantic chunks.
- embeddings.py — transforms text into vector embedding's.
- vectorstore.py – stores embedding's.
- retriever.py — collects relevant context.

This pipeline offers semantic retrieval based on user queries and assessment context [2].

3.11. Rag Execution Flow

User input or system requirement is recognized 2. Relevant documents are obtained from vector store. Retrieved content is inserted into the LLM prompt. LLM generates grounded, context-aware output. This ensures that the learning content created remains:

- Accurate
- Domain-aligned
- Personalized
- Explainable

4. System Workflow And User Interaction Model

- This section outlines the whole operational workflow of the proposed AI-powered personalized learning and career advancement platform. The workflow is aimed to emulate real-world job counselling and individualized education processes
- utilizing artificial intelligence and massive language models [4].

The system runs through a sequential and adaptive pipeline, where the output of each stage becomes the input for the next level. This ensures continual customization throughout the user journey

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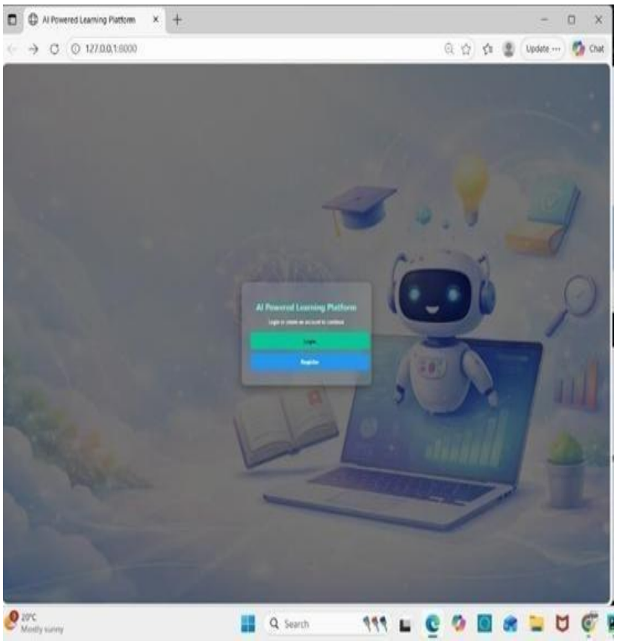

Figure 2 AI-Powered Personalized

4.1.User Entry And Authentication Workflow

The concept begins with a centralized webpage which provides two basic options

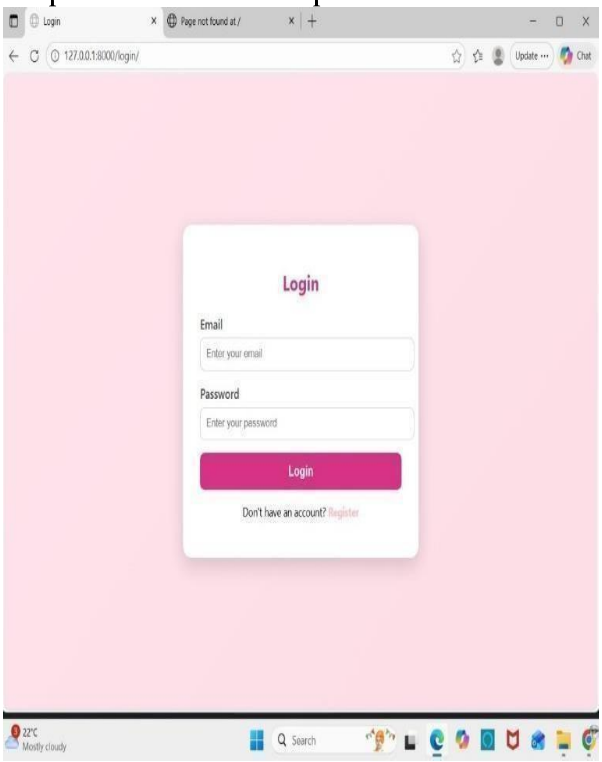

Figure 3 Existing user login

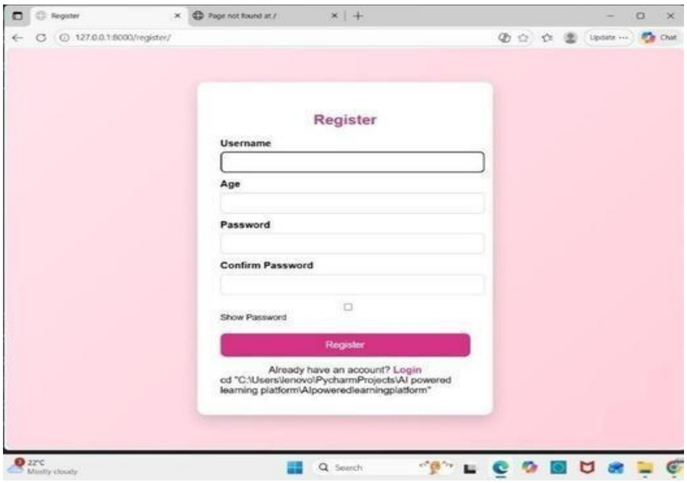

Figure 4: New User registration

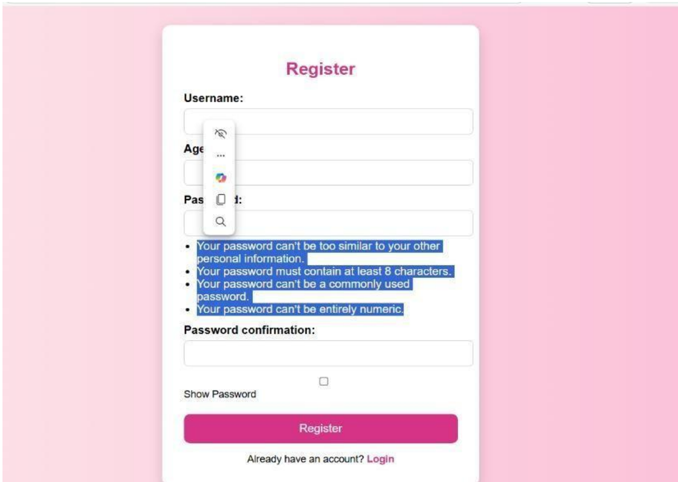

Figure 5: Registration

4.2.New User Registration

A new user is required to register by providing:

- Email ID
- Age
- Secure password

Age information plays a key role in establishing the psychological maturity level and difficulty of assessment questions. After successful registration, the user is sent to the login interface credentials. Upon successful login [5]:

- A unique session identification is produced User profile data is initialized.

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- Learning history and prior assessments are recovered.

This session-based method offers continuity and personalization across many user engagements [6].

4.3.Initial Psychometric Assessment Trigger

Once the user signs in for the first time, the system automatically launches the psychometric testing module. Unlike typical aptitude systems that use predetermined multiple-choice questions, the suggested platform employs LLM-driven adaptive psychometric inquiry.

The purpose of this stage is to:

- Understand user personality traits.
- Identify behavioral tendencies.
- Analyze decision-making patterns Capture inherent career interests.

5. Model [Adaptive Psychometric Question Generation]

5.1.Indirect psychological questioning approach

Traditional psychometric exams often fail because users intentionally strive to choose "correct" responses. To circumvent this shortcoming, the system utilizes indirect psychological inquiry, similar to approaches employed by psychologists and psychotherapists [7].

Examples include:

- Situational reasoning questions
- Behavioral reflection prompts
- Hypothetical real-life circumstances

This strategy offers deeper psychological analysis without explicit trait disclosure

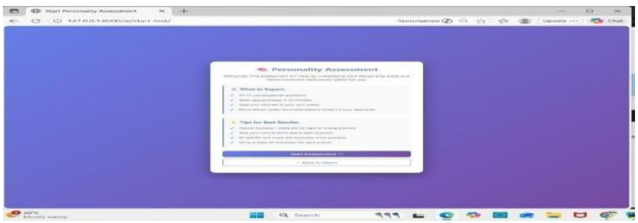

Figure 6: **Indirect psychological questioning**

5.2.Llm-Based Dynamic Question Generation

The backend employs the QWEN (Queen Bit) 5.0 Large Language Model to dynamically generate psychometric questions. Each question is produced depending on:

- Previous user answers
- Emotional tone of the answer
- Behavioral patterns found
- Trait theories formed so far

The assessment comprises of 10 to 15 adaptive questions, where:

- No two users receive identical question sets
- Question difficulty and depth evolve dynamically
- Later inquiries depend on prior behavioral clues

This adaptive questioning closely mirrors genuine human therapy sessions.

5.3.Question Flow Control And Error Handling

Since question generating is accomplished dynamically through an LLM, the system includes numerous reliability mechanisms:

- Prompt validation rules
- Structured response formatting
- Fallback question templates
- Session-level consistency tests If any LLM response fails validation, the system automatically regenerates the question using alternate prompt instructions, guaranteeing ongoing assessment flow.

6. Personality Trait Analysis And User Classification

6.1.Trait Extraction Methodology

Each user reaction is evaluated to obtain psychological markers such as:

- Analytical thinking capacity
- Creativity orientation
- Leadership tendency
- Emotional intelligence

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- Adaptability
- Risk tolerance
- Learning motivation

Semantic reasoning and weighted evaluation are used by the system to translate textual replies into normalized trait scores.

6.2. Personality Profiling

After completion of the psychometric assessment, the platform generates a full personality characterization including:

- Dominant personality attribute
- Secondary supporting traits
- Behavioral inclinations
- Learning behavior patterns Strengths and developing areas this classification forms the psychological foundation for all later recommendations.

6.3. Career Recommendation Engine Trait-To-Career Mapping Logic

The career recommendation module integrates:

- Psychological trait scores
- User interest patterns
- Cognitive strengths
- Industry role requirements

The system does not rely on static mapping tables alone. Instead, the LLM performs reasoning-based matching between personality profiles and profession domains.

6.4. Career Recommendation Output

Based on the analysis, the system generates Four to five individualized career recommendations each recommended career includes:

- Career description
- Required technical and soft skills
- Justification based on user traits
- Learning pathway overview

6.5. Career-Specific Skill Assessment Module

Once the user selects a preferred professional domain, the system conducts a career-specific evaluation. This assessment evaluates:

- Foundational domain knowledge
- Logical problem-solving ability
- Conceptual understanding
- Practical familiarity
- The assessment questions are again dynamically generated using the LLM and are matched with real industry expectations.

6.6. Skill Level Classification

Based on evaluation performance, users are divided into:

- Beginner
- Intermediate
- Advanced

This classification determines:

- Course depth
- Learning complexity
- Project difficulty

7. Personalized Course Generation Using Rag

7.1. Retrieval-Augmented Generation (Rag) Concept

To ensure correctness and reliability in content generation, the platform leverages Retrieval Augmented Generation (RAG).

RAG combines:

- Information retrieval from verified knowledge sources
- LLM-based reasoning and generation
- This strategy avoids delusion and increases educational quality

7.2. Rag Training Workflow

The backend architecture includes:

- train.py for prompt-based learning
- client.py for LLM communication
- engine.py as the central reasoning engine

The system retrieves:

- Career-specific curriculum topics
- Industry skill frameworks
- Practical learning objectives

The collected content is injected into LLM prompts before generation

7.3. Course Structure Generation

Based on skill level and career option, the algorithm generates:

- Module-wise learning structure

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- Learning objectives per module
- Theory explanations
- Practical tasks
- Real-world case studies
  Each user receives a fully tailored learning plan.

7.4.Practical And Theoretical Learning Integration

The platform stresses balanced learning by combining:

- Knowledge of conceptual theory
- Useful practical exercises both employability and information retention are enhanced by this dual-mode learning.

7.5.Capstone Project And Github Submission

At the completion of all modules, the system assigns a **career-specific capstone project**.
Project characteristics include:

- Real-world problem statements
- Industry-relevant objectives
- Mandatory GitHub repository submission This ensures
- Practical skill validation
- Portfolio development
- Job-readiness assessment

7.6.Learning Analytics And Continuous Personalization

The platform continuously monitors:

- Learning progress
- Assessment trends
- Skill improvement rate
- User engagement behavior Based on analytics, the system can:

Modify learning tempo

- Recommend revision modules
- Suggest advanced topics

This generates a continuously adapting learning environment.

7.7.Advantages Of The Proposed Workflow

- Fully tailored learning experience AI-driven psychological analysis
- Adaptive career discovery
- Industry-aligned course generation
- Reduced learning mismatch
- Improved career clarity

7.8.Research Significance

This research adds to:

- AI-based psychometric modeling
- Personalized education systems
- Career intelligence platforms
- LLM-driven adaptive learning frameworks

The suggested solution bridges the gap between psychological assessment and technical skill development within a single AI-driven architecture.

8. Limitations Of The Proposed System

Although the proposed AI-powered personalized learning and career enhancement platform demonstrates strong effectiveness, certain limitations must be acknowledged:

- Dependence on Large Language Model reasoning may lead to minor contextual ambiguity in complex responses.
- Text-based psychometric assessment accuracy depends on user expression quality.
- Large-scale deployment may introduce latency due to real-time LLM inference.

8.1. Data Privacy And Ethicalaspects

By guaranteeing transparency, user autonomy, and non-deterministic recommendations, the system adheres to ethical AI principles. Clinical diagnosis is avoided in all assessments, which are advisory in nature. There is no third-party data sharing and user data is safely stored using encrypted methods.

8.2.Evaluation Of Performance And System Efficiency

Engagement levels, consistency of trait extraction, relevance of career recommendations, and alignment between skill level and generated course difficulty were used to assess system performance. Compared to conventional MCQ-based systems, the results show higher engagement.

8.3.Future Improvements And Scope

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This research presented an AI-powered personalized learning and career enhancement platform integrating psychological assessment, career recommendation, and adaptive course generation using LLMs and RAG. The system overcomes limitations of static counselling approaches by providing reasoning-based mapping and skillaligned learning paths. Future enhancements include integration of real- time labor market data, explainable AI modules, multimodal assessments, long-term personality tracking, and AI-based mentorship systems.

8.4.Applications And Real-World Impact

The platform bridges the gap between learner personality and career pathways and is applicable to education, corporate training, online learning platforms, and workforce development initiatives

Summary

The system was evaluated based on user engagement, personality profiling accuracy, career recommendation relevance, and alignment between skill levels and generated learning paths. Users showed higher engagement with adaptive questioning compared to traditional multiple-choice systems. The reasoning-based mapping enhanced by the alignment between user Interests and recommended careers. RAG-based generation reduced hallucination, ensured domain alignment, and maintained appropriate difficulty levels. The modular architecture provided stable and flexible system performance despite minor latency during real-time inference.

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