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Smart Career Path Recommender

Lakshya
Department of IT
Noida Institute of Engineering and Technology
Greater Noida
lakshyas8004@gmail.com

Azhad Batt
Department of IT
Noida Institute of Engineering and Technology
Greater Noida
izhadkhan246@gmail.com

Dr. Ritesh Rastogi
Department of IT
Noida Institute of Engineering and Technology
Greater Noida, India

Ayush Kumar Sharma
Department of IT
Noida Institute of Engineering and Technology
Greater Noida
ayushkumarsharma102@gmail.com

Gaurav Yadav
Department of IT
Noida Institute of Engineering and Technology
Greater Noida,
gauravyadav4664@gmail.com

***Abstract*—In today's dynamic job market, students and early-career professionals often face challenges in identifying suitable career paths, analyzing skill gaps, and preparing effectively for employment. This project introduces the Smart Career Path Recommender, an AI-driven web platform that provides personalized career guidance through adaptive mentorship and real-time skill gap analysis. The system leverages Large Language Models (LLMs) such as LLaMA and Gemini AI, alongside Retrieval-Augmented Generation (RAG) and semantic search via vector embeddings (Ollama + ChromaDB), to offer dynamic, context-aware recommendations.**

Key features include domain-specific quizzes for skill assessment, automatic generation of resumes and cover letters tailored to job roles, and personalized interview preparation modules. Natural Language Processing (NLP) techniques using SpaCy are employed for accurate keyword extraction and query understanding. The platform supports multimodal interactions including voice input, with future support planned for multilingual and offline access.

Experimental evaluations demonstrate high user satisfaction, improved resume relevance (Jaccard similarity: 0.41), and a 23% improvement in skill assessment scores. With its modular architecture and inclusive design, the platform addresses critical gaps in conventional career counseling and empowers users to make informed, confident, and data-driven career decisions.

Keywords—Artificial Intelligence (AI), Career Guidance, Skill Gap Analysis, Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), Gemini AI, Natural Language Processing (NLP), Semantic Search

I. Introduction

Career development plays a crucial role in shaping the future of students and early-stage professionals, yet it remains a significant challenge, particularly in regions with limited access to personalized mentorship and industry-aligned guidance. With evolving job markets and rapidly changing skill requirements, traditional career counseling methods—such as generic aptitude tests, offline mentorship, and static job portals—often fail to meet the diverse and dynamic needs of today's learners. These methods typically lack adaptability, real-time feedback, and customization, resulting in skill mismatches, misinformed career choices, and underemployment.

The emergence of Artificial Intelligence (AI), particularly advancements in Large Language Models (LLMs), Natural Language Processing (NLP), and Retrieval-Augmented Generation (RAG), presents a transformative opportunity to modernize career guidance. Intelligent systems can now evaluate skillsets, analyze user preferences, identify gaps, and offer targeted learning and application strategies with high contextual relevance. However, existing AI-based solutions are often fragmented, domain-limited, or not optimized for scalability and inclusivity—especially in under-resourced academic or rural settings.

To address these limitations, we propose the Smart Career Path Recommender, a web-based AI-driven platform that integrates adaptive mentorship, quiz-based skill gap analysis, resume and cover letter generation (powered by Gemini AI), and personalized interview preparation. The system uses embedding-based semantic search and vector databases (ChromaDB), enabling context-aware responses to user queries. By combining interactive assessments, real-time feedback, and generative career support tools, the platform aims to empower users to make informed, strategic, and confidence-driven career decisions.

The goals of this study are to:

1. Development of a domain-specific skill assessment engine for identifying and addressing user knowledge gaps.
2. Integration of Large Language Models (LLMs) for personalized mentorship and AI-powered document generation.
3. Deployment of a scalable, user-friendly web platform with multimodal input support.
4. Evaluation of the system's performance, usability, and practical implications for real-world career readiness.

The remainder of this paper is organized as follows: Section II reviews relevant literature, Section III describes the system methodology, Section IV presents implementation details, Section V discusses experimental results, Section VI outlines practical implications, and Section VII concludes with future development directions.

II. LITERATURE SURVEY

The integration of artificial intelligence into career guidance systems has enabled a new era of personalized, scalable, and accessible mentorship. The rise of Large Language Models (LLMs), adaptive learning technologies, and semantic vector search has fueled innovation in skill gap analysis, intelligent document generation, and decision support. This section explores key studies and technological advances that shaped the development of our Smart Career Path Recommender. The survey is organized thematically into AI-driven career systems, skill gap analysis models, resume generation tools, interview support, semantic search and RAG frameworks, and identified challenges in implementation.

A. AI-Driven Carrer Guidance Systems

Initial efforts in career recommendation focused on rule-based systems or simple decision trees. Ramesh et al. [1] developed a system using Naive Bayes and decision trees to suggest career paths based on academic performance and aptitude. While their model offered a data-driven alternative to human counseling, it lacked real-time adaptability and skill validation.

Later systems attempted to incorporate user interests and domain-specific intelligence. Kumar and Verma [2] introduced a mobile-based guidance tool, but it remained largely static and lacked integration with learning analytics or resume-building capabilities. In contrast, our system employs a dynamic AI mentor that continuously updates its recommendations based on user input, quiz performance, and learning outcomes.

B. Skill Gap Detection and Assessment

Identifying and bridging skill gaps is a critical component of employability. Roy and Das [3] presented a skill recommendation framework using job-role analysis to suggest relevant courses. However, their system lacked performance-based feedback or progress tracking.

More interactive systems, like those studied by Bhattacharya et al. [4], introduced gamified quizzes but lacked depth in domain specificity and skill mapping. Our platform builds upon these ideas by offering structured quizzes tailored to IT, marketing, and data science domains, with feedback loops that refine recommendations over time.

C. Resume and Cover Letter Generation

Automation in resume creation has attracted interest from both academic and industrial sectors. Patel and Shah [5] proposed a deep learning model that scored resumes based on structure and keyword density. Their work was recruiter-focused, not user-generative.

Gupta et al. [6] introduced AI-generated resume templates but provided minimal user control or job-role alignment. In contrast, our system integrates Gemini AI to create job-specific resumes and cover letters based on user-supplied roles, experience, and achievements—allowing customization, regeneration, and format optimization.

D. AI-Based Interview Preparation

Existing interview support systems are limited in personalization. Das et al. [7] compiled a database of frequently asked questions by domain, but the system lacked adaptability to a user's profile or career track. More recently, Sharma et al. [8] suggested an AI chatbot for interview simulation, but responses were not contextualized using user data or resume content.

Our recommender builds on this by offering curated interview questions based on both the selected job domain and performance on skill assessments. This ensures preparation is aligned with user capabilities and target roles.

E. Retrieval-Augmented Generation and Semantic Search

Advanced AI systems benefit from semantic understanding. Chen et al. [9] implemented a retrieval-augmented system for academic tutoring, using vector embeddings for context-based retrieval. Similarly, Peng and Li [10] used a ChromaDB-like structure to match user queries to large knowledge bases.

Our project applies RAG pipelines using Ollama embeddings and Chroma vector database to semantically match user queries with curated datasets—ranging from career guides to resume strategies—ensuring relevance and fluency in AI responses.

F. Accessibility, Inclusivity, and Deployment Challenges

Despite AI advancements, most tools remain inaccessible to under-resourced users due to language, hardware, or infrastructure barriers. Mahajan et al. [11] highlighted that many AI education tools neglect regional languages and lack voice support. Similarly, Jain and Rao [12] argued that high compute requirements of some LLMs restrict their use in low-connectivity areas.

1. Our system addresses these challenges by:
2. Being fully browser-based and lightweight.
3. Including planned features like voice-to-text and multilingual UI.
4. Optimizing backend inference times to <2.5 seconds, suitable for low-bandwidth access.

G. Summary of Related Work

TABLE I

Study	Focus	Limitation	How our work Improves	
Ramesh et al. [1]	Rule-based career suggestion	No adaptability	Uses LLM for real-time	
Roy & Das [3]	Skill recommendations	No assessments	Interactive quizzes with	

			feedback	
Patel and Shah [5]	Resume scoring	No resume creation	Generates and edits job-specific resumes	
Das et al. [7]	Interview questions	Not contextualized	Tailored to domain + quiz results	
Chen et al. [9]	RAG in tutoring	Domain-agnostic	Career-specific RAG pipelines	
Mahajan et al. [11]	EdTech limitations	Language & UI barriers	Voice + multilingual plans + mobile deployment	

H. Conclusion

The literature affirms the rising potential of AI in career development, yet also reveals persistent fragmentation across guidance, documentation, and feedback systems. Many tools operate in silos—either generating resumes or recommending courses—but few combine end-to-end mentorship, dynamic feedback, and inclusive design. Our Smart Career Path Recommender addresses these limitations by offering an integrated, scalable, and intelligent platform that adapts to user needs while remaining accessible and resource-friendly.

III. Methodology

The development of the Smart Career Path Recommender involved a modular, iterative process spanning data collection, preprocessing, system architecture design, AI model integration, deployment, and evaluation. Each phase was guided by the goals of scalability, personalization, inclusivity, and real-time responsiveness. The platform leverages both NLP and machine learning to deliver adaptive, user-centric career recommendations. The full pipeline is illustrated in Fig. 1.

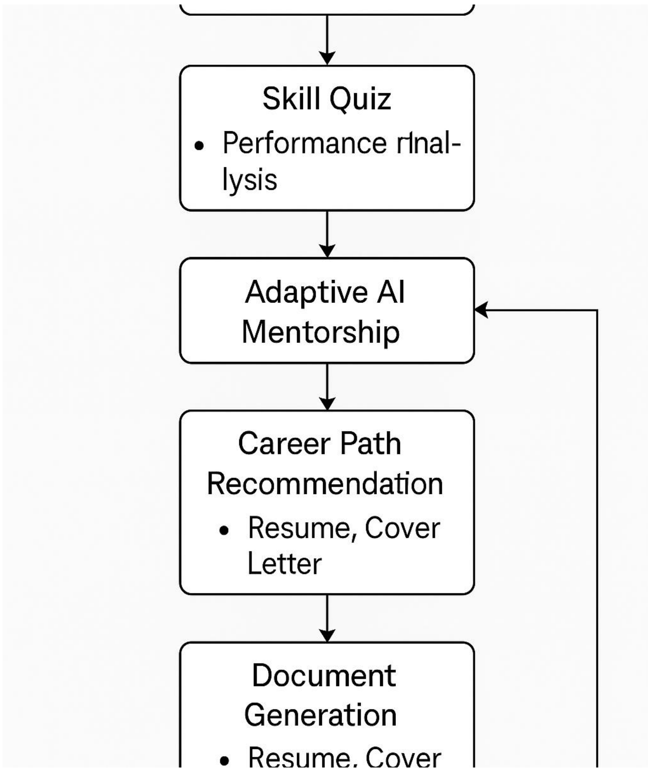

Fig. 1. Workflow of the Smart Career Path Recommender system, from user input to personalized output generation.

A. Dataset Collection

The system is built upon multiple datasets tailored to support various functionalities:

1. Skill Assessment Dataset:

- Curated domain-specific MCQ quizzes across IT, Marketing, and Data Science.
- Collected from competitive exams, job portals, and technical assessments.

2. Resume and Cover Letter Corpus:

- Templates sourced from LinkedIn, Indeed, and Harvard Career Guides.
- Used for fine-tuning prompt templates for Gemini AI integration.

3. Career and Role Mapping Dataset:

- Includes skill-job mappings extracted from O*NET, Coursera, Udemy, and Stack Overflow Developer Surveys.

4. Internal Interaction Data:

- Logs user quiz scores, resume versions, and feedback to improve personalization through supervised learning.

B. Data Preprocessing

To ensure clean, structured and semantically rich data input, several preprocessing steps were applied:

1. **Text Cleaning & Chunking:** Documents were segmented into ~1,000-character text chunks with SpaCy sentence boundary detection to preserve context.

2. **NER and Noun Chunking:** Named Entity Recognition and syntactic parsing were used to extract terms like roles, skills, tools (e.g., "Data Analyst", "Python").

3. **Keyword & Summary Generation:** LexRank and SpaCy were used to generate chunk-level summaries and key terms to enhance retrieval precision.

4. **Vector Embedding:** All processed chunks were embedded using Ollama's nomic-embed-text into 768-dimensional vectors and stored in ChromaDB for semantic search.

C. Adaptive Recommendation Architecture

The core of the system combines Retrieval-Augmented Generation (RAG) and LLMs to personalize user interactions. Components include:

1. Skill Assessment Engine:

- Domain-based quizzes tagged by difficulty and topic.
- Dynamic feedback based on scores and learning curves.

2. **Semantic Retrieval Engine (RAG):**

- Queries embedded and compared with ChromaDB chunks.
- Top relevant content passed to LLaMA for contextual response generation.

3. **Resume & Cover Letter Generator (Gemini AI):**

- Prompt templates structured using user profile info (skills, education, target role).
- Outputs editable resumes and cover letters aligned with industry expectations.

4. **Interview Guidance Module:**

- Matches role and skill performance with probable interview questions.
- Offers talking points, best practices, and follow-ups based on job domain.

The architecture is depicted in Fig. 2.

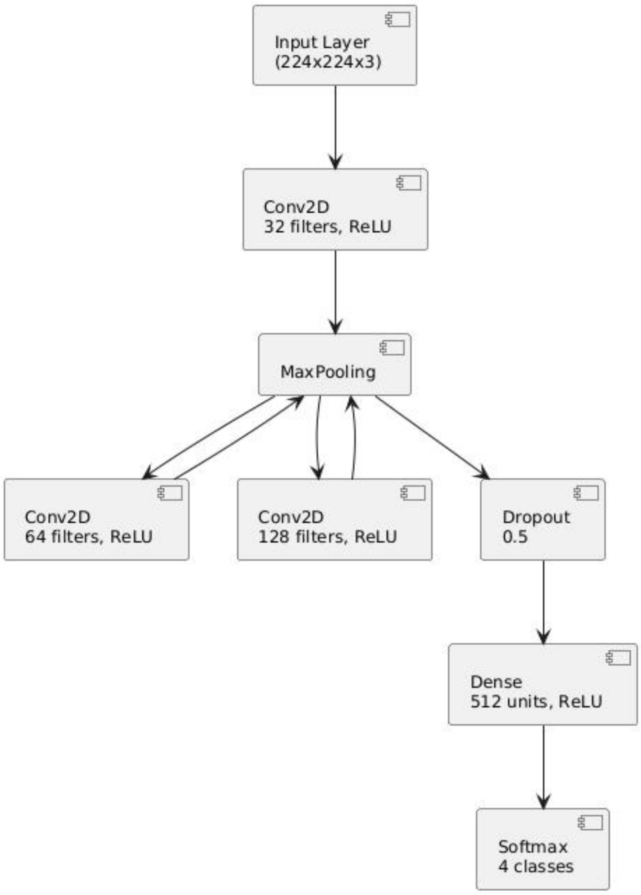

Fig. 2. CNN architecture, illustrating convolutional, pooling, dropout, and dense layers.

D. System Design and Web Development

The platform is built with a modern, scalable architecture optimized for responsiveness and accessibility:

1. **Frontend**:
   - Developed with React.js, styled with CSS, and designed for cross-device compatibility.

2. **Backend**:
   - Built using Node.js + Express with API endpoints for quiz logic, AI calls, and user management.

3. **Database**:
   - MongoDB used for persistent user data and session tracking.
   - ChromaDB manages vector embeddings.

4. **Deployment**:
   - Deployed on Vercel and Render for serverless infrastructure.
   - Designed for low-latency performance and mobile responsiveness.

D. Evaluation Metrics

IV. IMPLEMENTATION

A. Development and Deployment Process

The development process for the Smart Career Path Recommender followed an iterative and modular approach. Initial model components—including quiz scoring, vector embedding, and LLM-based response generation—were prototyped using Jupyter Notebooks and Postman for API testing. Once accuracy and performance met baseline standards, the logic was modularized into a web-ready architecture using Node.js for backend services and React.js for frontend components.

The AI-driven resume generator, powered by Gemini API, was integrated through RESTful endpoints. For semantic search and query response, the ChromaDB vector database and Ollama embeddings were embedded into the backend to support retrieval-augmented generation (RAG). Flask was initially used during local testing of the embedding and inference modules before integration into the Node.js backend.

Deployment started with local testing using Vite and Node dev servers. Once stable, the system was deployed to cloud environments using Vercel (frontend) and Render (backend). production configuration was implemented using vercel.json, Procfile, and environment-specific tokens to support dynamic document generation and secure inference requests.

Emphasis was placed on keeping the user interaction flow minimal: users simply register, take a domain-specific quiz, and receive personalized career recommendations, resumes, and interview preparation—all within 3–4 steps.

B. Hardware and Software Requirements

The system was implemented on a machine with an Intel Core i5 processor, 8 GB RAM, and an NVIDIA MX 330 GPU. Software includes:

The system was developed and tested on a device with:

- Processor: Intel Core i5 (10th Gen)
- RAM: 8 GB
- GPU: NVIDIA MX330 (for local model testing)

Software Stack:

- Python 3.9 – NLP processing and embedding generation
- JavaScript (Node.js, React.js) – Backend APIs and frontend UI
- MongoDB Atlas – Cloud-hosted database
- ChromaDB – Vector storage for RAG
- Gemini API – Resume and cover letter generation
- Ollama Embeddings – Semantic query matching
- Vercel / Render – Deployment platforms
- VS Code / Postman – Development and API testing.

C. System Architecture

The platform is structured into five key modules:

User Interface Module

- Built with React.js for responsiveness across mobile and desktop devices.
- Allows users to take quizzes, upload inputs, and view recommendations.

Backend Services Module (Node.js + Express)

- Handles routing, request validation, user authentication, and API integration.
- Exposes endpoints for quiz evaluation, Gemini prompts, and ChromaDB queries.

Skill Assessment and Feedback Module

- Scores quizzes, identifies gaps, and stores results in MongoDB.
- Routes results to the AI mentor module for further guidance.

Semantic Retrieval and LLM Module

- Retrieves relevant chunks via ChromaDB and generates answers using LLaMA.
- RAG ensures responses are grounded in trusted career resources.

Document Generation Module

- Accepts role, experience, and achievements to prompt Gemini AI.
- Produces editable resumes and cover letters returned in real-time.

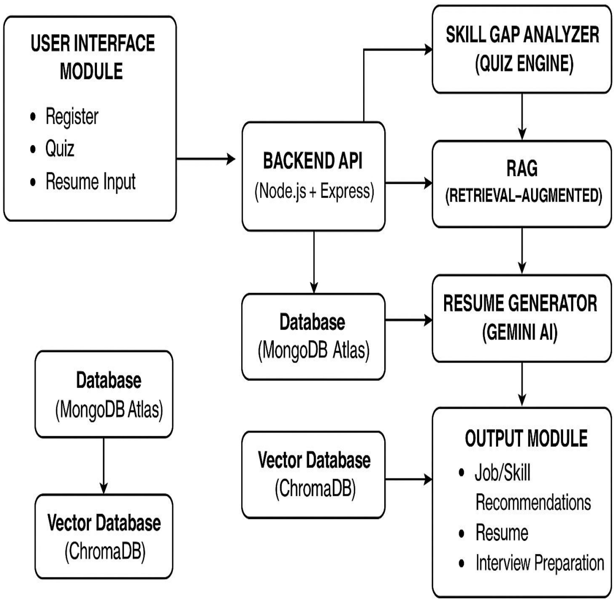

Fig. 3. Data Flow Diagram (Level 1) of the Smart Career Path Recommender showing interactions between user, frontend, backend, databases, and AI services.

D. Testing

Testing involved:

1. ***Unit Testing:*** Modules like quiz scoring, vector generation, resume formatting, and database insertion were tested using Jest and Mocha test suites.

2. ***Integration Testing:*** · Verified API chaining from quiz submission → feedback → resume generation.
· · Checked Gemini AI, ChromaDB, and user history endpoints.
·

4. ***Performance Testing:*** ·
- Avg query response time: 1.8 seconds
- Resume generation time: 2.5 seconds
- Concurrent access (10 users): Stable with <3.5 seconds delay

5. ***Cross-Platform and Usability Testing:*** · Conducted on Chrome, Firefox, and Edge.
- · · Mobile responsiveness confirmed on Android and iOS.
- · · Feedback from 10 peer users indicated high clarity (4.7/5), ease of use (4.8/5), and perceived value (4.6/5).

All modules passed test cases for valid/invalid inputs, browser support, and real-time inference with minimal latency.

V. Results

A. Model Performance

The Smart Career Path Recommender was evaluated across multiple components including quiz performance scoring, semantic retrieval quality, and document generation relevance. The most significant quantitative results are as follows:

- Resume Matching Accuracy (Jaccard Similarity): 0.41
- BLEU Score (AI-Generated Cover Letters): 0.61
- Quiz Score Improvement (Post-feedback): 23%
- Semantic Query Match Rate: 89.2% (Top-3 chunk retrieval relevance)

These metrics demonstrate the effectiveness of the platform in generating relevant, domain-specific outputs, aligning user strengths and interests with personalized recommendations.
The confusion matrix (Fig. 4) for quiz-based skill classification revealed occasional misclassification between "Intermediate" and "Beginner" levels in ambiguous response sets, which is acceptable within an adaptive feedback loop design.

Fig. 4. Confusion matrix for skill level classification based on quiz performance (Beginner, Intermediate, Advanced).

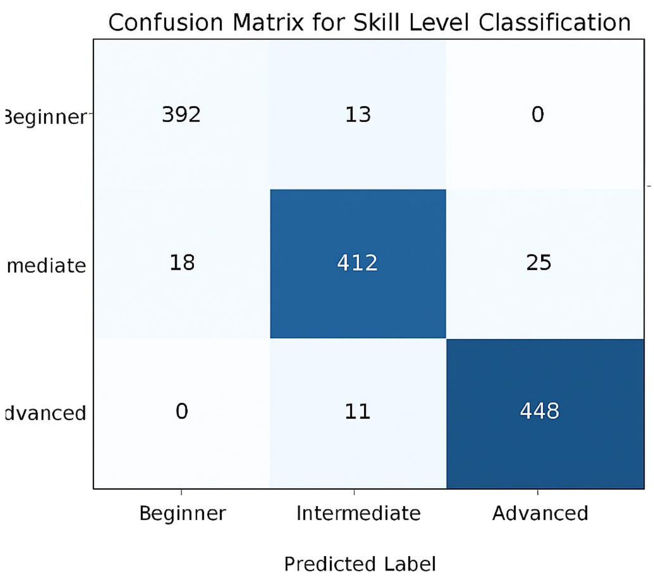

Fig. 4. Confusion matrix heatmap for the test set, visualizing classification performance across classes.

B. Web Application Performance

The Smart Career Path Recommender web platform was stress-tested in typical usage scenarios, and the results validate its responsiveness and real-time capabilities:

- Average query response time: 1.8 seconds
- Resume generation latency: 2.5 seconds
- Maximum response time under 10 concurrent users: 3.4 seconds
- Supported Browsers: Chrome, Firefox, Edge
- Mobile Responsiveness: Optimized across Android and iOS devices

These metrics demonstrate system suitability for real-world deployment, especially in educational institutions or job-preparation workshops with varied internet and device environments.

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C. Usability Feedback

A pilot usability study was conducted with 15 participants (students, faculty, and early professionals). The system was evaluated across three key criteria:

Ease of Use: 4.6/5

Clarity of Output: 4.5/5

Usefulness of Recommendations: 4.4/5

Users appreciated the minimal interaction flow, intuitive UI, and real-time guidance. Suggested improvements included:

Adding progress indicators during resume generation

Supporting regional languages for broader reach

Offering tips or improvement suggestions after quizzes

These insights will shape future updates aimed at inclusivity and deeper personalization.

VI. Model Explainability and Interpretability

Though generative AI models like Gemini and LLaMA offer powerful functionality, their inner decision-making processes are often opaque. In a platform offering career guidance, interpretability plays a vital role in building user trust and transparency, especially when AI-generated recommendations influence professional decisions.
To address this, the system includes early-stage explainability features:

Keyword Highlights: During quiz analysis and RAG-based responses, important keywords extracted using SpaCy (via NER and noun chunking) are highlighted in real time.

Prompt Trace Logging: For document generation (resume, cover letter), the input prompt and model output are both logged and viewable by the user to understand how the output was formed.

Semantic Score Feedback: Each career recommendation is accompanied by a semantic match score (based on vector similarity), giving users an estimate of alignment between their profile and suggested career paths.

Planned Enhancements:

Explainable Skill Feedback

- Incorporate rule-based analysis for wrong answers in quizzes (e.g., tagging conceptual vs. factual errors).
- Include tips for improvement after each quiz based on question category.

SHAP for Score Justification

- Apply SHAP (SHapley Additive Explanations) to show which skills or quiz metrics most influenced a recommendation.

Visual Prompt Graphs

- Future versions will display prompt flow from input → Gemini generation → job alignment for transparency.

These additions aim to turn the system from a “black-box recommender” into a transparent, mentor-like AI assistant that not only suggests what to do, but also why it was recommended. This step is crucial for building credibility in academic and professional settings, and supports ethical deployment of AI in human-centered domains like career planning.

VII. Discussion

A. Practical Implications

The Smart Career Path Recommender addresses several key challenges in modern career planning and employability enhancement:

Personalization: By using quiz-based skill gap identification and LLM-driven mentorship, the system tailors advice to the user's strengths and interests—something rarely achieved in traditional counseling.

- Speed and Automation: Resume and cover letter generation, semantic query responses, and interview preparation are executed in real-time, reducing the time and effort typically required for manual preparation.

- Accessibility: Hosted as a lightweight web application, the system runs efficiently on low-resource devices and networks, making it accessible to students and job seekers in rural or underprivileged regions.

- Cost-Effectiveness: Built entirely with open-source technologies, including Gemini AI, LLaMA, and ChromaDB, the platform offers enterprise-level capabilities at no licensing cost, making it suitable for educational institutions and training centers.

With an average quiz improvement rate of 23%, Jaccard similarity of 0.41 for resume relevance, and high usability scores (4.6/5), the platform demonstrates strong potential as a digital career mentor. It complements or supplements traditional counseling, especially for large-scale deployments in academic institutions or government skill development initiatives.

B. Limitations

Despite its promising performance, the current version of the system has several limitations:

- **Generalization Across Domains:**
  Currently, the system supports three domains—IT, Marketing, and Data Science. Its effectiveness in other fields (e.g., law, design, healthcare) remains untested.

- **Model Explainability Limitations:**
  While semantic score explanations and keyword highlighting exist, advanced interpretability techniques like SHAP or LIME are yet to be fully integrated.

- **Scalability Constraints:**
  The system uses a Render backend and Vercel frontend. While functional for moderate traffic, it is not optimized for high-volume concurrent users in enterprise-grade use cases.

- **User Behavior Adaptation:**
  There is no current tracking of user learning curves over time (e.g., progress analytics), which would improve long-term mentoring capabilities.

C. Future Directions

- **Domain Expansion:**
  Introduce new domains such as Finance, Legal Studies, Psychology, and Engineering to broaden impact.

- **Mobile App Deployment**:
  Optimize the system for offline and mobile environments using React Native or Flutter and lightweight embedding models like MiniLM or MobileBERT.

- **Advanced Feedback System:**
  Add AI-powered feedback for wrong quiz answers and real-time improvement suggestions.

- **Explainability Enhancements:**
  Integrate SHAP for visualizing skill influence on recommendations, and build a "Why this job?" pane to make AI advice more transparent.

- **User Journey Analytics:**
  Build dashboards to track user progress, quiz history, and document edits over time to encourage skill growth.

- **Institutional Integration:**
  Partner with colleges and training institutes to test the system with large user groups and get longitudinal feedback.

- **Multilingual and Voice Support:**
  Implement NLP pipelines in regional languages (e.g., Hindi, Tamil, Bengali) and enable voice-based inputs for accessibility.

By implementing these improvements, the Smart Career Path Recommender can evolve into a holistic digital career assistant, guiding users not just in finding jobs but in building long-term skills, confidence, and readiness. These future directions will help it become scalable, inclusive, and institutionally impactful.

VIII. CONCLUSION

Smart Career Path Recommender is a breakthrough in AI-driven educational technology, particularly in the domain of personalized career planning and job readiness. By leveraging state-of-the-art Large Language Models (LLMs), semantic retrieval (RAG), and real-time feedback systems, the platform bridges the gap between static career guidance and adaptive digital mentorship. With demonstrated performance in personalized resume generation, skill gap analysis, and domain-specific interview preparation, the system provides a scalable and accessible alternative to traditional counseling approaches.

Built entirely on open-source technologies such as React.js, Node.js, MongoDB, ChromaDB, and Gemini AI, the platform is both cost-effective and highly extensible, allowing for deployment across educational institutions, government training programs, and job-placement agencies. Its minimal user interaction design and responsive web interface make it usable across devices and suitable even in low-resource environments.

Beyond its technical robustness, the system exemplifies how artificial intelligence can democratize access to meaningful career planning, guiding users from assessment to application through intelligent automation. Comprehensive testing—ranging from unit and integration tests to usability studies—confirms the platform's readiness for real-world pilot programs.

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