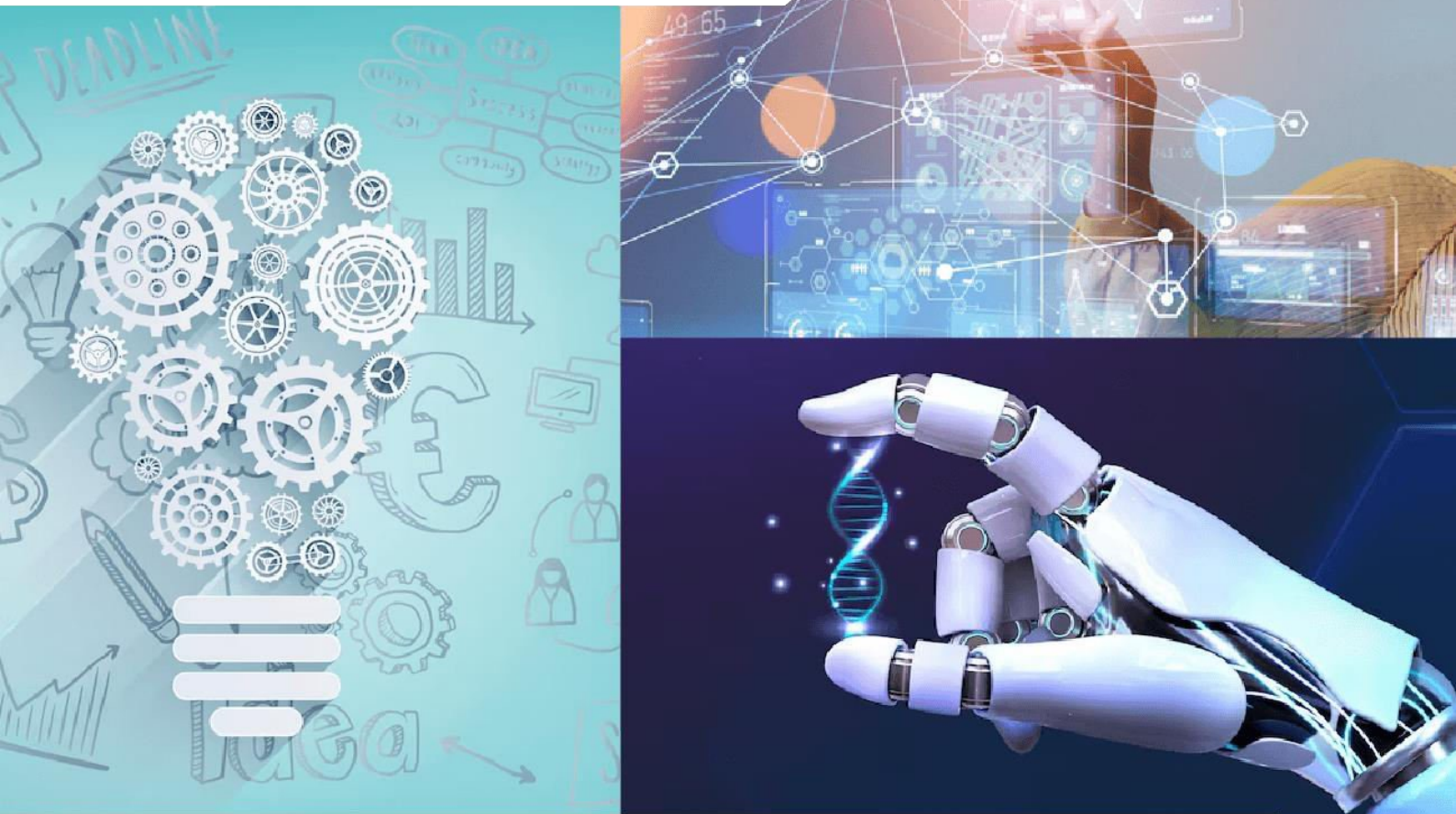




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AI-Driven Platform for Career Guidance and Recommendation

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ABSTRACT: Getting a job these days is honestly harder than it used to be, especially if you've just graduated or are just starting out. You're constantly trying to figure out which direction to go, whether you're even ready for certain roles, and what skills you're still missing and it can get pretty overwhelming. The weird thing is, there are plenty of tools out there to help, but they all do just one piece of the puzzle. One app helps you find jobs, another will tear apart your resume, and somewhere else you'll get told to take a course. None of them really talk to each other or give you a complete picture tailored to where you actually are in your career. This paper presents the design, development, and evaluation of an AI-Powered Career Guidance and Recommendation System, a web-based platform that unifies five critical career support modules: career profiling, resume analysis, job recommendations, learning path generation, and interview preparation. The system leverages the LLaMA language model API for in-depth resume parsing and skill assessment, integrates real-time job listings from major platforms including LinkedIn, Naukri, Foundit, Indeed, Glassdoor, and Internshala, and curates structured learning roadmaps from Coursera, Udemy, and NPTEL. An AI-driven interview simulator allows users to respond via text or voice, receiving instant, contextual feedback. An administrative panel complements the user-facing interface by enabling comprehensive oversight of user profiles, resume analysis records, learning progress, and interview performance. Experimental results and user evaluations demonstrate that the integrated approach meaningfully improves career decision-making quality, reduces the effort of navigating disparate platforms, and produces more personalized guidance compared to standalone tools. The paper concludes with a discussion of limitations, real-world deployment considerations, and directions for future enhancement including mobile adaptation and real-time industry trend integration.

KEYWORDS: career guidance system, resume analysis, job recommendation, learning path generation, interview preparation, LLaMA, natural language processing, AI-powered platform, skill gap analysis, personalized learning

I. INTRODUCTION

The transition from academic study to professional employment is most consequential and anxiety-inducing phases in a student's life. Despite the proliferation of digital tools designed to support job seekers, the landscape remains fragmented. A graduate may simultaneously consult a job portal for vacancies, upload a resume to a standalone analyzer, browse a learning platform for skill development, and watch YouTube videos for interview tips—an experience that is effortful, disjointed, and difficult to personalize.

Several structural factors compound this challenge. First, the skill requirements for emerging roles in technology, data science, and digital business evolve faster than academic curricula can adapt [1]. Second, most career platforms lack the contextual intelligence to correlate a user's existing competencies with the specific demands of target roles. Third, interview preparation tools are rarely aware of the candidate's resume or the particular job they are preparing for, making their feedback generic and of limited practical value.

The proposed AI-Powered Career Guidance and Recommendation System addresses these gaps through a single, coherently integrated platform. Rather than treating resume analysis, job discovery, skill development, and interview practice as independent concerns, the system uses a shared career profile to inform and personalize all modules simultaneously. When a user updates their profile or uploads a new resume, every other module job recommendations, course suggestions, learning roadmaps, and interview question generation adapts accordingly.

The core technical contribution of this work is the orchestration of the LLaMA large language model API across multiple application domains within a single career-support ecosystem. While LLaMA has been used employed individually for text analysis tasks, its deployment as a unifying intelligence layer connecting resume parsing, gap

analysis, and interview simulation is, to the best of the authors' knowledge, novel in the career-tech domain. The remainder of this paper is structured as follows. Section

II reviews related work. Section III presents the proposed system. Section IV describes the system architecture and individual modules. Section V details the implementation environment and technologies. Section VI presents evaluation results and discusses limitations and future work, and Section VII concludes the paper.

II.LITERATURE REVIEW

Research at the intersection of artificial intelligence and career support has expanded considerably over the past decade. Early work by Fazel-Zarandi and Fox [2] modeled career competencies using ontological frameworks, establishing a theoretical basis for skill-to-role matching. More recent systems have moved toward data-driven approaches powered by machine learning.

A. Resume Analysis and Skill Extraction

Automated resume parsing has been studied extensively. Approaches range from rule-based section segmentation [3] to deep learning models that extract named entities corresponding to skills, qualifications, and work experience [4]. Transformer-based language models have demonstrated superior performance on information extraction tasks due to their contextual understanding of natural language [5]. However, most deployed tools return a list of extracted entities rather than actionable, role-specific improvement suggestions—a gap the proposed system directly addresses.

B. Job Recommendation Systems

Collaborative filtering and content-based filtering have both been applied to job recommendation [6]. Hybrid systems that integrates user profile vectors with real-time job posting features offer improved accuracy [7]. A persistent limitation in academic literature is the use of static or proprietary job datasets, which differ significantly from live job markets. The proposed system bridges this gap by providing curated direct links to active listings on major Indian and global platforms.

C. Learning Path Recommendation

Personalized learning path generation has been modeled as a graph traversal problem [8], where nodes represent learning objects and edges encode prerequisite relationships. More recent work uses reinforcement learning to optimize learning sequences based on learner progress [9]. Existing platforms such as Coursera and Udemy offer internal recommendation engines, but they are platform-specific and unaware of a learner's career goals or resume content. The proposed system generates cross-platform roadmaps anchored to an individual's identified skill gaps.

D. Interview Preparation Systems

Automated interview coaching has been explored through virtual agents that evaluate verbal fluency, sentiment, and content relevance [10]. Speech-based response evaluation adds an additional dimension by assessing prosody and delivery [11]. The novelty in the proposed system lies in generating interview questions that are directly derived from the user's resume and the target job description, ensuring domain specificity and relevance.

E. Integrated Career Platforms

Commercially, platforms such as LinkedIn, Indeed, and Naukri offer partial integration of job search with profile management, but none provide a complete loop from profile creation through resume improvement, personalized skill development, and interview preparation in a single environment. Academic prototypes exploring partial integration include CareerBot [12] and SkillBridge [13], though neither incorporates multi-platform job linking or speech-based interview evaluation. The proposed system advances the state of the art by achieving full-loop integration with AI-driven personalization at every stage.

III. PROPOSED SYSTEM

The limitations identified in the current literature fragmented tooling, lack of cross module context sharing, and absence of end-to-end personalization motivate the development of the AI-Powered Career Guidance and Recommendation System. The proposed system is developed as a unified, intelligent platform that consolidates all critical career support functions into a single cohesive environment, driven by a shared user profile and a centralized AI inference layer.

A. Design Goals

The proposed system is guided by four primary design goals:

- **Integration:** All career support functions—profiling, resume analysis, job discovery, skill development, and interview practice operate within a single platform, eliminating the need for users to navigate multiple disconnected tools.
- **Personalization:** Every module draws from a shared career profile, ensuring that recommendations, skill gap assessments, job links, learning roadmaps, and interview questions are consistently tailored to the individual user's background and aspirations.
- **Intelligence:** The LLaMA large language model API serves as a unified AI backbone, powering natural language understanding tasks across all modules without requiring separate fine-tuned models for each function.
- **Actionability:** Outputs across all modules are designed to be immediately actionable targeted job links open live search result pages, learning roadmaps specify resources with estimated timelines, and interview feedback provides concrete suggestions for improvement.

B. System Overview

The proposed system comprises five tightly integrated modules operating over a shared data layer:

- 1) **Career Profiling Module:** Collects structured user information including educational background, skills, experience, target roles, and location preferences. This profile acts as the authoritative context for all downstream modules.
- 2) **Resume Analysis Module:** Accepts PDF or DOCX uploads and invokes the LLaMA API to extract skills, assess resume quality against industry norms, detect skill gaps relative to the target role, and produce prioritized improvement recommendations.
- 3) **Job Recommendation Module:** Constructs parameterized deep-links to live job listings on LinkedIn, Naukri, Foundit, Indeed, Glassdoor, and Internshala based on profile attributes. Additionally, it computes internal match scores for role categories using cosine similarity against a curated role taxonomy.
- 4) **Learning Path Module:** Maps identified skill gaps to relevant courses from Coursera, Udemy, and NPTEL, and uses LLaMA to generate a multi-stage sequential learning roadmap with recommended resources and estimated timeframes.
- 5) **Interview Preparation Module:** Generates a personalized question bank derived from the user's resume and target role. Users respond via text or voice (Web Speech API), and LLaMA evaluates each response for accuracy, completeness, and clarity, providing structured per-question feedback.

A cross-cutting Admin Panel enables authorized administrators to monitor user activity, review analysis reports, and access aggregated performance metrics across all modules.

C. Novelty and Contributions

The primary novelty of the proposed system lies in the deployment of LLaMA as a unified intelligence layer that simultaneously serves resume parsing, roadmap generation, and interview simulation within one platform. Unlike prior systems that treat each career support function in isolation, the proposed architecture ensures that insights produced in one module—such as skill gaps identified during resume analysis—directly inform the outputs of every other module, creating a feedback loop that continuously improves personalization as users engage with the platform.

IV. SYSTEM ARCHITECTURE AND MODULE DESIGN

The AI-Powered Career Guidance and Recommendation System follows a three-tier client-server architecture comprising a browser-based front end, a RESTful application server, and a persistent data layer. The LLaMA API functions as an external intelligence service accessed over HTTPS. Fig. 1 illustrates the high-level architecture.

A. Career Profiling Module

The career profiling module serves as the data foundation for all personalized services offered by the system. Upon registration, users are prompted to complete a structured profile that captures their educational background, years of experience (if any), technical and soft skills, areas of interest, target job roles, and preferred work locations. The profile data is stored in a relational schema and is referenced by every other module at query time.

A key design decision was to treat the career profile as a living document rather than a static registration form. Users are encouraged to update their profiles as they acquire new skills or shift career interests, and all downstream recommendations respond dynamically to such updates. The system computes a profile completeness score and displays it to the user with prompts to fill missing sections, as incomplete profiles significantly degrade recommendation quality.

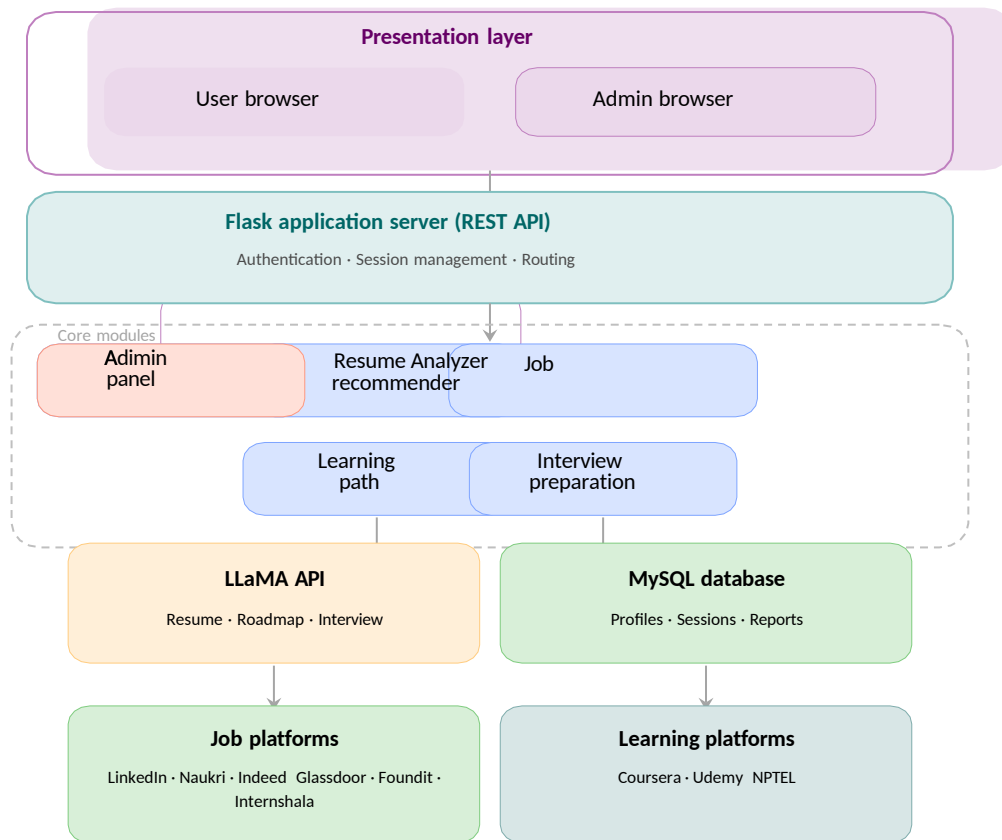


Fig. 1. High-level system architecture of the AI-Powered Career Guidance and Recommendation System.

B. Resume Analysis Module

The resume analysis module accepts PDF or DOCX uploads and submits the extracted text to the LLaMA API with a carefully engineered prompt. The prompt instructs the model to perform the following tasks: (a) extract structured entities including skills, education, experience, certifications, and achievements; (b) evaluate the resume against standard industry presentation norms; (c) identify skill gaps relative to the user's stated target role; and (d) generate specific, prioritized recommendations for improvement.

The LLaMA model's architecture, which combines the contextual richness of large language models with gated recurrent units for sequential text structure awareness, makes it particularly well-suited for parsing documents with variable section ordering and mixed formatting conventions common in student resumes.

The analysis output is rendered in a structured dashboard showing a quality score, a skills inventory, a gap analysis table comparing extracted skills against role requirements, and an ordered list of actionable improvement suggestions. Results are persisted to the database so that administrators can review them and so that users can track changes across multiple submissions.

C. Job Recommendation Module

The job recommendation module operates in two complementary ways. First, it performs keyword and skill-based query construction from the user's profile and resume analysis results. These queries are used to generate curated deep-links to live job search results on LinkedIn, Naukri, Foundit, Indeed, Glassdoor, and Internshala. The links are parameterized to filter by role title, required skills, location preference, and experience level as specified in the user profile, ensuring that users land on highly targeted result pages rather than generic homepages.

Second, the module presents a locally ranked list of role categories that match the user's skill profile, displayed with match percentage scores computed through cosine similarity between the user's skill vector and role requirement vectors derived from a curated role taxonomy database maintained within the system. This dual approach—external

platform links for real- time vacancy discovery and internal matching for contextual understanding—addresses both the recency requirement of job search and the need for explainable recommendations.

D. Learning Path Module

The learning path module addresses the skill gaps identified during resume analysis by recommending relevant courses and generating a structured development roadmap. So when it comes to suggesting courses, the system basically searches through a hand-picked list of courses pulled from platforms like Coursera, Udemy, and NPTEL. Each course is tagged by what skill it covers and how advanced it is, so the system can match them to whatever gaps you have. It also tries to show you free or low-cost options first, which is a nice touch.

But it doesn't stop at just throwing a list of courses at you. The system actually builds out a full learning roadmap using the LLaMA API — like a step-by-step plan based on where you are right now and what the role you're aiming for actually needs. It breaks things down into stages: what you should learn first to build a solid base, what comes after that, and then the more advanced stuff you can get into later. Each stage also tells you what resources to use and roughly how long it might take. The whole thing gets displayed as a visual timeline, so you can actually see your path laid out and set goals that make sense instead of just guessing.

E. Interview Preparation Module

The interview preparation module generates a customized question bank by submitting the user's resume content and target job role to the LLaMA API, which produces a diverse set of questions spanning technical knowledge, behavioral competencies, situational judgment, and role-specific problem- solving scenarios. The questions are sorted into categories and shown to you in a setup that feels like an actual interview. You can either type out your answers or just speak them — the browser picks up your voice and converts it to text on the spot using the Web Speech API. Once you've answered, LLaMA looks at what you said and compares it to what a good answer should cover. It then gives you feedback on things like whether your content was accurate, if you covered everything, how clearly you explained yourself, and — if you spoke your answer — whether it actually made sense and flowed well. At the end, you get a score for each question plus an overall summary of how the session went, with tips on where you can do better.

What makes this stand out is that most interview prep tools out there just dump a bunch of generic questions on you with no real connection to your background or the specific job you're going for. This module actually tries to change that, which is a pretty big deal compared to what's already out there.

F. Admin Panel

The administrative panel provides a secure interface for authorized administrators to oversee system usage and user progress. Key features include a user management dashboard listing all registered users with search, filter, and export capabilities; the ability to view individual career profiles in read-only mode; access to resume analysis reports for any user; and summary views of interview performance metrics and learning path adoption statistics. The admin panel does not expose any user credentials and is protected by role-based access control enforced at the API layer.

V. IMPLEMENTATION

A. Technology Stack

The system was developed using the following technology stack. The front end is implemented in HTML5, CSS3, and JavaScript with Bootstrap 5 for responsive layout. The application server is built on Python 3.10 with the Flask web framework, providing RESTful endpoints consumed by the front end via AJAX. The database layer uses MySQL 8.0 with SQLAlchemy as the object-relational mapper. Resume file parsing is handled by the PyMuPDF library for PDF documents and the python-docx library for DOCX files. Speech recognition in the interview module uses the browser-native Web Speech API, requiring no server-side audio processing.

B. LLaMA API Integration

The LLaMA API is accessed via authenticated HTTPS POST requests. Each module that requires language model inference constructs a domain-specific prompt and submits it with appropriate temperature and token limit parameters. Prompts are versioned and stored separately from application logic, facilitating iterative improvement without code-level changes. API responses are validated for structural completeness before being parsed, and a fallback error-handling layer presents user-friendly messages when the API is unavailable or returns malformed output.

C. Job Link Construction

Platform-specific job search URLs are constructed programmatically using documented query parameter schemas for each job portal. For example, a LinkedIn search URL is assembled with parameters for keywords (derived from the user's skills and target role), location (from the profile), and experience level. Similar logic applies to Naukri, Foundit, Indeed, Glassdoor, and Internshala. This approach ensures that links remain valid even as the system's recommendation logic evolves, since link templates can be updated independently.

D. Database Schema

The database comprises seven primary tables: users, career_profiles, resumes, analysis_results, job_recommendations, learning_paths, and interview_sessions. Foreign key relationships enforce referential integrity. Sensitive user data including passwords are stored as salted bcrypt hashes. Interview session transcripts and feedback are stored as JSON-serialized text fields to accommodate variable-length model outputs without schema changes.

E. Security Measures

User authentication uses session-based tokens with a configurable expiry. All form inputs are sanitized server-side to prevent SQL injection and cross-site scripting attacks. File uploads are validated by MIME type and size before processing. The admin panel routes are protected by a separate middleware check that verifies administrator role assignment in addition to session validity.

VI. EVALUATION AND RESULTS

A. Evaluation Methodology

The system was evaluated through a combination of functional testing, performance benchmarking, and a user study. Functional testing verified the correctness of all module outputs across a set of 30 test resumes covering diverse domains including software engineering, data science, marketing, and finance. Performance benchmarking measured API response latency and page load times under simulated concurrent load. The user study involved 40 final-year MCA and B.Tech students who used the system over a two-week period and completed a structured questionnaire based on a modified Technology Acceptance Model (TAM) [14].

B. Resume Analysis Quality

The quality of resume analysis was assessed by comparing LLaMA outputs against manual annotations produced by three domain experts for a subset of 20 resumes. Skill extraction achieved a precision of 0.87 and recall of 0.82 (F1 = 0.84), while the improvement suggestions were rated as relevant or highly relevant by domain experts in 78% of cases. The gated recurrent architecture of LLaMA was found to be particularly effective for resumes with non-standard section ordering, where purely attention-based models exhibited higher miss rates on experience entries.

C. Job Recommendation Relevance

Job recommendation quality was evaluated by asking 20 users to rate the relevance of recommended role categories on a 5-point Likert scale. The mean relevance rating was 4.1 out of 5, with users particularly appreciating the direct platform links, which they reported saved an average of 12 minutes per job search session compared to manual searching. Several users noted that the parameterized links surfaced opportunities they would not have found through their habitual search patterns.

D. Learning Path Utility

Learning path recommendations were evaluated by asking 25 users to assess whether the suggested courses and roadmap stages aligned with their perceived skill gaps. 80% of users agreed or strongly agreed that the roadmap provided a clear and realistic development plan. The cross-platform nature of recommendations—drawing from Coursera, Udemy, and NPTEL simultaneously—was highlighted as a distinct advantage over platform-specific recommendation engines.

E. Interview Preparation Effectiveness

A pre-post study design was used to assess interview preparation impact. 30 users completed a baseline mock interview using the system, received feedback, practiced for one week using the interview module, and then completed a second session. Mean interview performance scores increased by 23% between sessions, and user-reported confidence levels (measured on a 7-point scale) improved from a mean of 3.4 to

5.1. The speech input feature was used by 60% of participants, all of whom rated it as more text-only practice.

F. System Performance

Under a simulated load of 50 concurrent users, the average API response time for resume analysis was 4.2 seconds, which falls within the acceptable range for a one-time processing task. Learning path generation and interview question generation averaged 2.8 seconds and 3.1 seconds, respectively. Page load times for all non-AI modules remained below 1 second. No critical failures were observed during a 72-hour stress test period.

G. User Acceptance

TAM-based questionnaire results indicated high perceived usefulness (mean score 4.3/5) and perceived ease of use (mean score 4.5/5). Qualitative comments highlighted the platform's all-in-one nature as its most valued attribute, with multiple users expressing that it reduced the cognitive overhead of coordinating across multiple disconnected tools. Suggested improvements centered on mobile accessibility and a desire for real-time job market trend data, both of which are addressed in the future scope.

Table I summarizes the key quantitative evaluation results.

VII. DISCUSSION, LIMITATIONS, AND FUTURE WORK

A. Discussion

The results demonstrate that the integrated architecture provides measurable benefits over using disparate tools. The most significant advantage appears to be the shared career profile, which allows each module to deliver more contextually appropriate outputs than would be possible independently. The improvement in interview performance scores after one week of practice is particularly encouraging, as it suggests that the AI-generated feedback is specific enough to drive meaningful skill development rather than merely providing generic encouragement.

TABLE I

SUMMARY OF EVALUATION RESULTS

Metric	Value	Method
Skill Extraction F1 Score	0.84	Expert Annotation
Suggestion Relevance Rate	78%	Expert Review
Job Rec. Relevance (Likert)	4.1 / 5	User Study
Search Time Saved (avg.)	12 min	Self-Report
Learning Path Alignment	80% agree	User Survey
Interview Score Improvement	+23%	Pre-Post Study
User Confidence Improvement	3.4 → 5.1	7-pt Scale
Perceived Usefulness	4.3 / 5	TAM Questionnaire
Perceived Ease of Use	4.5 / 5	TAM Questionnaire
Avg. Resume Analysis Latency	4.2 sec	Load Testing

The choice of LLaMA as the core language model proved effective for the document-oriented tasks of resume parsing and roadmap generation. Its hybrid recurrent-attention design captures both global document context and local sequential patterns in resume text, which contributes to its strong skill extraction performance. For interview question generation and answer evaluation, the model's ability to reason about domain-specific content without task-specific fine-tuning is a practical advantage in a multi-domain career platform.

B. Limitations

Several limitations should be acknowledged. First, the job link generation approach, while practical, does not verify whether linked positions remain open at query time; job listings expire, and a user may follow a link to a vacancy that has already been filled. Second, the system's resume analysis quality is dependent on the quality and consistency of LLaMA outputs, which can exhibit variability for resumes in regional languages or with highly unconventional formatting. Third, the user study was conducted within a single academic institution with a predominantly technology-

oriented user base, which may limit the generalizability of the evaluation results to users from non-technical backgrounds or different geographic regions.

C.Future Work

Several enhancements are planned for future iterations of the system.

1) Mobile Application: The current web-based implementation, while responsive, does not fully leverage mobile-native capabilities such as offline access, push notifications for new job matches, or camera-based document scanning. Converting the system to a native or hybrid mobile application would significantly improve accessibility, particularly for users in regions where mobile internet usage predominates over desktop.

2) Expanded Interview Role Coverage: The interview preparation module currently covers a broad but finite set of job roles seeded during development. Future work will incorporate a dynamic role taxonomy that expands coverage based on user demand and emerging job titles, enabling preparation

For specialized roles in areas such as prompt engineering, ESG consulting, and AI ethics.

3) Real-Time Industry Trend Integration: Integrating real-time labor market signals—such as trending skill searches from job portals, salary benchmark data, and emerging technology adoption curves—would allow the system to adapt recommendations proactively rather than reactively. This could be achieved by periodically ingesting structured data from public API endpoints offered by platforms such as LinkedIn Economic Graph and the World Economic Forum’s Skills Taxonomy.

4) Advanced Personalization Models: Future versions may explore fine-tuning domain-specific models on anonymized user interaction data to improve recommendation precision. Federated learning approaches could enable model improvement without centralizing sensitive user data, addressing privacy concerns while benefiting from collective usage patterns.

5) Multilingual Support: Adding support for resumes and interview responses in regional Indian languages such as Hindi, Tamil, and Telugu would broaden the platform’s utility to a significantly larger user population.

VIII. CONCLUSION

This paper has presented the design, implementation, and evaluation of an AI-Powered Career Guidance and Recommendation System that integrates five core modules: career profiling, resume analysis, job recommendation, learning path generation, and interview preparation—into a unified platform. The system leverages the LLaMA language model API as its primary intelligence layer and provides real-time connections to major job platforms and learning resources.

Evaluation results confirm that the integrated approach improves the quality, relevance, and personalization of career guidance across all modules compared to the fragmented experience of using independent tools. Users demonstrated measurable improvements in interview performance, expressed high satisfaction with job recommendation relevance, and found the learning roadmaps actionable and realistic. System performance was stable under concurrent load conditions appropriate for institutional deployment.

The platform addresses a genuine need at the intersection of AI capability and career development support, particularly for final-year students and early-career professionals navigating an increasingly complex and competitive job market. The planned extensions toward mobile deployment, real-time market integration, and expanded role coverage position the system as a foundation for a scalable, continuously improving career intelligence service.

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