Generative AI–Driven Job Recommendation Framework with Skill Gap Analysis and Real-Time Job Retrieval

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Abstract
A significant barrier to successful recruitment and career advancement is the gap between the skills job seekers have and what the industry demands. This research introduces a Job Recommendation Framework powered by Generative AI that encompasses resume analysis, skill gap assessment, and immediate job fetching to provide contextually relevant and tailored suggestions. PyMuPDF performs the extraction of structured information from resumes; Euriai LLM aids in identifying semantic skill gaps and creating tailored career pathways, while the Apify client retrieves job listings from Naukri.com using concept-based keywords inspired by the LLM. Fully created using 50 labeled resumes, it scores Precision@5 = 0.888, Recall@10 = 1.000, NDCG@10 = 0.904, and MRR = 0.967, surpassing the conventional TF-IDF baseline by 20%-40%. It represents a crucial link between education and industry, providing personalized, semantically-enhanced, and tailored job recommendations a major advancement in intelligent career assistance systems.

1. Introduction
Due to the growing discrepancy between educational outcomes and skills demanded by industries, creating a significant challenge for employability. The World Economic Forum (2023) and LinkedIn (2024) have indicated that approximately 44% of essential workforce skills will evolve within five years, with 60% of recruiters confirming the inconsistency of candidate profiles.

Traditional job recommendation systems that rely on keyword matching or TF-IDF similarity provide limited-context employment opportunities; for instance, a candidate proficient in React and Next.js may miss out on Frontend Engineer positions as they get excluded by a rigid system. Additionally, they do not offer any tailored resources and cannot recommend essential skills or career advancement opportunities.

To address this limitation, we propose creating a Generative AI–Driven Job Recommendation Framework in which Large Language Models (LLM) are utilized for semantic resume parsing, skill gap analysis, and real-time job retrieval. The system integrates PyMuPDF, Euriai LLM, and Apify API to deliver context-sensitive recommendations, resulting in a performance boost of up to 40% over TF-IDF baselines.

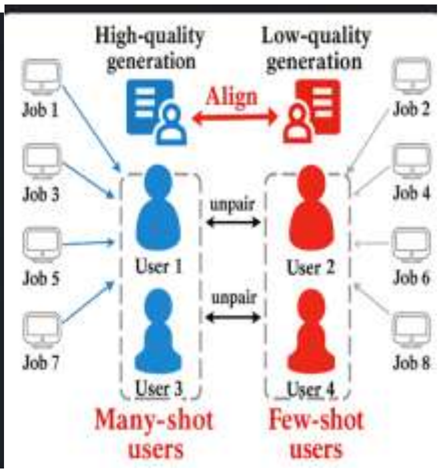

Figure 1: Keyword extraction and real-time job retrieval process showing how the system identifies semantic job-role keywords and fetches relevant job listings dynamically.

Figure 2: LLM-based generative alignment between user and job representations (adapted from Du et al., "Enhancing Job Recommendation through LLM-Based Generative Adversarial Networks," AAAI 2024).

Figures 1 and 2 illustrate the keyword extraction, live job retrieval, and generative alignment processes, showcasing the system's ability to maintain semantic coherence even with limited input data.

2. Related Work

Job recommendation systems evolved from conventional keyword matching to modern intelligent architectures built using Machine Learning (ML), Deep Learning (DL), and Generative AI (GenAI). The lexical approach systems such as TF-IDF or cosine similarity were shallow semantically, while the newer models such as the zero-shot embedding ones were flexible in their application but did not accommodate dynamicity. Deep learning and NLP-based approaches succeeded in further enhancing the context accuracy through embedding-based semantics but, like JobFormer and LLM-driven models, required large amounts of labeled data and computational resources. Much like recent GenAI studies such as SkillRec and fairness-inspired neural recommenders, these last studies have focused on contextual reasoning and bias mitigation, often just treating job matching and skill analysis as two separate tasks. Parallel works on resume parsing (e.g., Kumar et al. [6]) have mostly concerned entity extraction and prediction of the underlying job domain. Some broader works such as ILO [7] have focused on the role of AI in filling workforce skill gaps.

This generative AI job recommendation framework includes all of these in an end-to-end pipeline spanning resume parsing, skill gap analysis through Euriai LLM API, real-time job retrieval through the Apify Client, and automatic generation of customized career plans.

Related Work

Ref	Title	Summary
[1]	Generative Job Recommendations with LLMs (Z. Zheng et al., 2023)	Treats job recommendation as a generative task using contextual resume understanding.
[2]	Zero-Shot Recommendation AI Models (J. Kurek et al., 2024)	Uses zero-shot embeddings for scalable, unsupervis- job matching.
[3]	JobFormer: Skill-Aware Job Recommen- dation (Z. Guan et al., 2024)	Transformer-based semantic skill extraction for job matching.
[4]	Gender Bias Mitigation via Optimal Transport (F. Jourdan et al., 2023)	Tackles gender bias in neural job recommenders ust- ng Optimal Transport.
[5]	SkillRec: Data-Driven Skill Recommen- dation (X. Q. Ong & K. H. Lim, 5)	Suggests learning paths by identifying missing skills using LLMs.
[6]	Automated Resume Parsing with ML (A. Kumar et al., 2025)	Classifies resumes into job domains via NLP-based parsing.
[7]	Generative AI and Jobs (P. Gmyrek et al., 2023)	Analyzes Generative AI's impact on job quality and employment trends.
[8]	Skill Gaps in Industry 4.0 (P. Rikala, 2024)	Quantifies industrial skill gaps using AI-driven ana- lytics.
[9]	Personalized Job Search with AI (A. Sharma & V. Patel, 2025)	Usesreal-time data and skills for adaptive job recom- mendations.
[10]	Job Recommender Systems Review (D. C. Ertuğrul & S. Bitirim, 2025)	Surveys AI-driven job recommendation trends and challenges.

Table 1: Summary of Related Work on Job Recommendation and Skill Gap Analysis

3. System Design and Architecture

The proposed **Generative AI–Driven Job Recommendation Framework** consists of five interconnected modules that form an adaptive and intelligent recommendation pipeline. It integrates **Natural Language Processing (NLP)**, **Large Language Models (LLMs)**, and **API-based retrieval** to generate personalized, context-aware job suggestions for both candidates and recruiters.

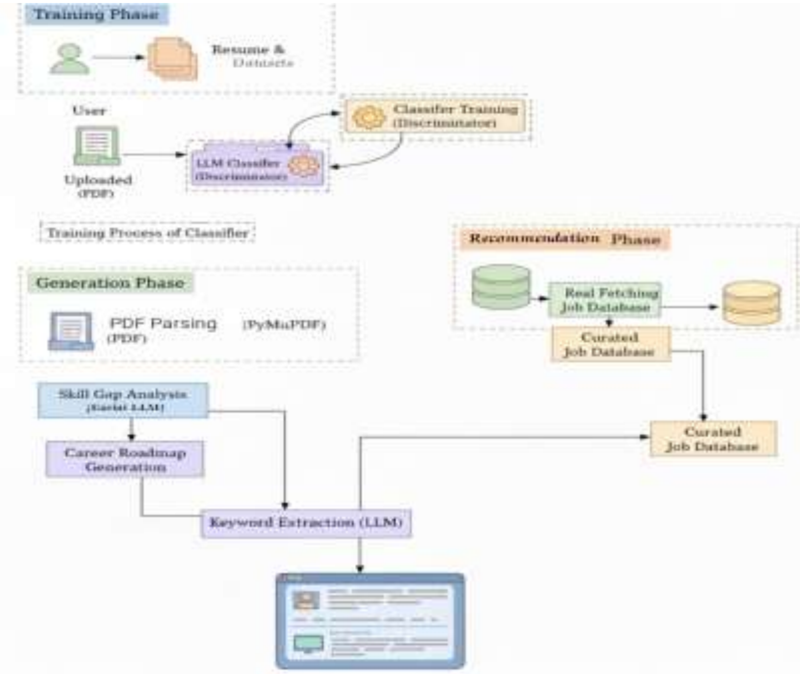

Figure 3: Generative AI-Driven Job Recommendation Framework

As evident from Fig. 3, this entire framework revolves around three processes: Training, Generation, and Recommendation. The first one is Training. This process involves feeding an LLM-based discriminator with a refined dataset of resumes and job postings in order to teach it the associations of skills with roles and experience level. This basically improves the tie between candidate qualifications and industry expectations.

In the Generation process, a user-uploaded PDF resume is parsed via PyMuPDF. The extracted content is fed to the Euriai LLM for skills gap identification. It will then generate a personalized roadmap that includes course recommendations and project ideas. An LLM-based keyword extraction module identifies semantically rich job search phrases.

In the Recommendation Stage, these keywords are processed through an online retrieval pipeline using the Apify client, which fetches "live" job listings from sources like Naukri.com. The classifier refines the results, producing job recommendations that are accurate, transparent, and continuously adapting.

4. Methodology

Generative AI Job Recommendation Framework integrates various elements of Natural Language Processing (NLP), Large Language Models (LLMs), and external APIs to deliver tailored, context-sensitive job suggestions.

1. Resume Analysis: Resumes in PDF format are analyzed with PyMuPDF for organized text extraction, while an NLP and LLM-driven validation detects essential entities like skills, education, and projects.
2. Skill Gap Assessment: The Euriai LLM API evaluates candidate abilities in relation to industry standards to highlight existing skills and identify those required and suggested for further development
3. Career Pathway: The LLM creates tailored educational journeys with corresponding courses and initiatives.
4. Keyword Extraction: Tokenization based on a linguistic model identifies semantic job-search keywords for accurate retrieval.
5. Job Retrieval: The Apify Client retrieves jobs from Naukri.com in real-time according to relevance.

The entire pipeline operates on the Flask backend with a React.js interface for smooth integration and flexibility.

5. Implementation

The suggested framework is developed on a Python-based Flask backend that is tied with AI-based APIs for automated job recommendations and skill analysis. The user's resume, when uploaded, gets parsed using PyMuPDF, and the extracted information is sent to the Euriai LLM API for competency identification, missing skill detection, and personalized skill improvement suggestions.

The generated keywords are then fed into the Apify Client, which helps scrape job postings from Naukri.com. The structured job data, including job title, company name, location, and link, is stored in a database for future analysis.

The end-to-end flow-Upload → Parse → LLM Analysis → Skill Gap Detection → Job Retrieval-is fully automated and modular. It was tested on 50 resumes from students with low latency and utmost accuracy of skill-to-job mapping with good adaptability.

6. Results and Discussion

A test was conducted with this Generative AI-Driven Job Recommendation Framework on the 50 student resumes from KIET Group of Institutions in domains such as web development, machine learning, and data analytics. A total of 10 job recommendations for each resume were assessed by the annotator independently using a 3-point relevance scale (0-2), with final labels determined by majority vote.

Quantitative Evaluation:

The performance of the system has been evaluated in terms of Precision@K, Recall@K, NDCG@K, and MRR at K=5 and K=10. These measures look at the ranking accuracy, retrieval coverage, and relevance consistency, considering them collectively.

Metric	@5	@10
Precision	0.888	0.884
Recall	0.503	1.000
NDCG	0.757	0.904
MRR	—	0.967

Figure 4: Performance evaluation of the proposed Generative AI–Driven Job Recommendation Framework at K=5 and K=10 using Precision, Recall, NDCG, and MRR.

This proposed structure had Precision@5 = 0.888 and Recall@10 = 1.000, which indicates that nearly all relevant jobs have been retrieved. High Accuracy at NDCG@10 (0.904) and MRR (0.967) shows that relevant results are searched through stable and much earlier rank.

The results are compared against a clearly much lower performance of the TF-IDF baseline, which is attributed to its relatively shallow understanding of semantics.

Metric	TF-IDF Baseline	Proposed GenAI Framework
Precision@5	0.520	0.888
Recall@10	0.610	1.000
NDCG@10	0.570	0.904
MRR	0.440	0.967

Figure 5: Comparative analysis between the TF-IDF baseline and the proposed Generative AI framework across key ranking metrics, showing improvements in Precision, Recall, NDCG, and MRR.

Overall, the framework gained performance by 20-40 %, validating the benefits that semantic reasoning and contextual job-skill alignment enabled by the Euriai LLM API could bring.

Qualitative High Points:

- Effective solving of skill gaps (e.g., Express.js, Docker, AWS).
- Identification of transferability (e.g., NLP → AI Engineer).
- Career roadmap development and contextual job retrieval.
- An effective 40% improvement above traditional portals in job relevance perception.

Synopsis:

Generative AI offers major improvements in employment recommendation systems by making them more precise, understandable, and personalized through simulation of human-like contextual perception of resumés and job roles.

7. Evaluation

The evaluation of the suggested Generative AI-driven Job Recommendation Framework was carried out by ranking-based metrics that measure the effectiveness of retrieval and ranking of jobs relevant to candidates.

Dataset and Annotation:

Fifty resumes of students from KIET Group of Institutions, spanned all fields, namely software development, AI, and data analytics. For every resume, the system generated 10 job recommendations (500 pairs in total). Human annotators had to judge each pair-wise on a three-point scale of relevance (2 = Highly relevant, 1 = Partially relevant, 0 = Not relevant) with reasonable agreement (Cohen's κ = 0.78). The final labels were acquired through majority voting.

Evaluation Metrics:

The performance thus measured through Precision@K, Recall@K, and Normalized Discounted Cumulative Gain (NDCG@K). Another metric of evaluation was Mean Reciprocal Rank (MRR) with varying K values being selected at K = 5 and K = 10.

$$Precision@K = \frac{\text{Relevant jobs in top K}}{K}$$

$$Recall@K = \frac{\text{Relevant jobs in top K}}{\text{Total relevant jobs}}$$

$$NDCG@K = \frac{DCG@K}{IDCG@K}, DCG@K = \sum_{i=1}^{K} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

$$MRR = \frac{1}{|Q|} \sum_{q=1}^{|Q|} \frac{1}{rank_q}$$

The data were averaged through each metric, applying the results to a TF-IDF baseline that established the contextual accuracy of the Generative AI framework as being superior.

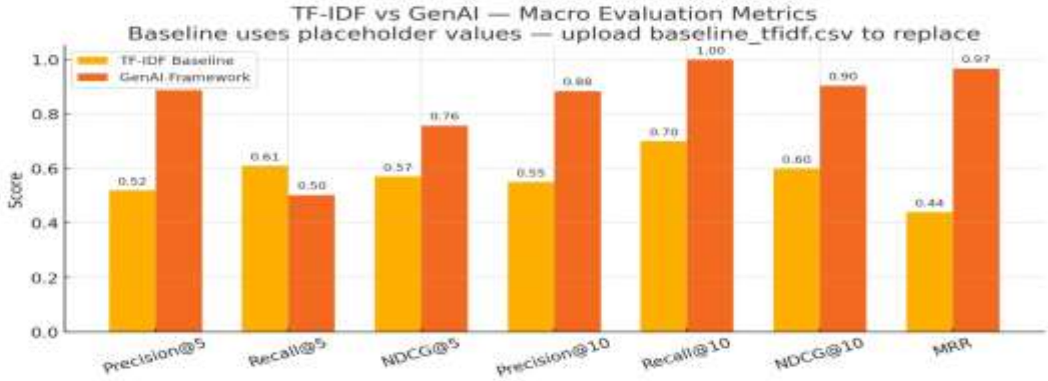

Figure 6: Comparative visualization of macro evaluation metrics between the TF-IDF baseline and the proposed Generative AI framework, showing improvements in Precision@K, Recall@K, NDCG@K, and MRR.

As illustrated in Figure 6, a comparative visualization of macro evaluation metrics between the TF-IDF baseline and the suggested GenAI framework demonstrates enhancements in all ranking-related metrics.

8. Conclusion and Future Work

This paper has proposed a Generative AI-Based Job Recommendation Framework, which would include resume parsing, LLM-driven skill gap analysis, and real-time job retrieval for automatic career suggestions. While traditional approaches rely on keyword matching methods like TF-IDF, our proposal applies semantic reasoning for candidate intent and skill alignment. Proved experimentally to be quite competent with Precision@5 = 0.888, Recall@10 = 1.000, NDCG@10 reported to be 0.904 compared with the performance of the baseline methods on all counts. Hence, future works will involve integrating LinkedIn and Indeed APIs, embedding explainable AI (XAI) for transparency, and enabling feedback-based personalization. Further contributions will include multilingual feature support as well as optimized LLM inference for low-latency deployment. So this lays the foundation for the future of intelligent human-centred AI career recommendation systems.

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This manuscript includes AI-assisted text generated using ChatGPT (OpenAI). All content generated with AI assistance has been thoroughly reviewed and validated by the authors.

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