

# AI Resume Builder and Career Recommendation System

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**Abstract** - This research introduces a dual-module framework comprising an AI-driven Resume Optimization Engine and a Semantic Career Recommendation System. The system architecture employs a high-fidelity AI Resume Builder that utilizes Natural Language Processing (NLP) for automated keyword optimization. Beyond static document generation, the framework features a Predictive Career Recommendation Engine that analyzes the semantic features of the user's profile to suggest personalized professional trajectories. Crucially, the system implements a Real-time API-driven Matching Module that filters live job and internship listings by calculating the Cosine Similarity between candidate resumes and specific job descriptions (JDs). By facilitating a direct transition from profile building to opportunistic placement, the proposed system minimizes the informational asymmetry in the entry-level labor market.

**Index Terms** - Keywords: Artificial Intelligence, Natural Language Processing (NLP), Recommender Systems, Resume Parsing, Semantic Matching, E-Recruitment.

## I. INTRODUCTION

The contemporary labor market is defined by a significant "visibility gap" between emerging talent and industrial opportunities. While the digitization of recruitment has led to an exponential increase in job listings, it has simultaneously created an environment of high-volume, low-relevance applications. For students and early-career professionals, the primary hurdle is Information Asymmetry: the inability to translate academic and project-based achievements into a machine-readable format that satisfies the rigorous criteria of modern Applicant Tracking Systems (ATS). This mismatch results in qualified candidates being prematurely filtered out by algorithms before a human recruiter ever evaluates their potential.

The core limitation of current market solutions is their fragmented nature. Most platforms exist either as static document editors or as isolated job boards, leaving a critical void in the "Resume-to-Employment" pipeline. A candidate may use one tool to build a resume and another to search for roles, but these systems rarely "communicate." There is a dire need for an integrated framework that not only facilitates the

construction of a professional profile but also performs Semantic Analysis to understand the user's core competencies and suggests a trajectory that aligns with their latent strengths.

Furthermore, the transition from profile creation to actual placement—specifically for internships—remains a daunting task for many. Manual searching is often inefficient and lacks the precision of data-driven matching. This "Placement Friction" occurs because candidates lack the tools to quantify how closely their specific skill set matches a particular Job Description (JD). To solve this, a unified system must employ Natural Language Processing (NLP) to act as a bridge, transforming the static text of a resume into a dynamic data vector that can be mathematically compared against real-time market opportunities.

This research proposes a holistic, End-to-End Vocational Navigation Framework designed to consolidate the professional lifecycle. The system utilizes an AI-driven architecture that begins with a high-fidelity Resume Parsing and Generation module. Using Named Entity Recognition (NER), the system extracts critical entities such as technical proficiencies, certifications, and project experience.

The primary contribution of this work is the development of a closed-loop system where the resume acts as the "Feature Input" for an automated Job Fulfillment Module. Unlike traditional methods, our approach ensures that every career recommendation is backed by a mathematical Cosine Similarity verification, providing users with a data-centric advantage in a competitive market.

## II. LITERATURE REVIEW

The digital transformation of the recruitment sector has catalyzed a transition from manual screening to automated, data-driven decision-making. Initial research in this domain focused primarily on keyword-based retrieval, which frequently yielded high false-positive rates due to the lack of linguistic context. As noted in early foundational studies, simple string-matching algorithms are incapable of distinguishing between the various semantic roles a keyword might play within a

curriculum vitae (CV).

Consequently, the academic community shifted toward Natural Language Processing (NLP) to decode the underlying intent and structure of professional documentation. The initial phase of automated recruitment relied heavily on rule-based systems and keyword matching. However, as noted in recent studies, these methods are structurally brittle and fail when encountering diverse document layouts. To address this,

Research has pivoted toward Natural Language Processing (NLP). By utilizing statistical models like Conditional Random Fields (CRF), researchers have been able to categorize text into logical segments. This shift allows for a more fluid extraction process that adapts to varying resume structures, transforming a static document into a structured data stream.

Recent literature highlights the use of Deep Learning architectures, specifically BERT (Bidirectional Encoder Representations from Transformers), to extract professional entities such as skills, education, and job titles. Studies indicate that a large percentage of qualified candidates are rejected due to a lack of semantic alignment between their resumes and job descriptions (JDs). Recent works have proposed "optimization loops" that provide real-time feedback to users. However, a common critique in the literature is that most existing builders are reactive—they fix errors rather than proactively aligning the candidate's profile with specific industrial requirements. Vocational guidance has evolved through the use of Recommender Systems.

Research generally splits these into content-based filtering (matching skills) and collaborative filtering (matching similar user paths). Hybrid models have emerged as the "Gold Standard," combining both approaches to solve the "Cold Start" problem for entry-level candidates. These systems analyze the latent features of a user's profile to suggest professional trajectories that are not just based on what they know, but what they can learn. The core of modern job-matching involves representing professional data in Vector Space. Researchers utilize the Cosine Similarity metric to calculate the mathematical proximity between a candidate's resume vector and a job description vector. This move beyond simple keyword matching allows systems to recognize synonyms and related roles (e.g., "Web Developer" vs. "Frontend Engineer").

Literature suggests that this mathematical objectivity reduces human bias in the shortlisting process and increases the precision of internship fulfillment. Despite the existence of high-quality parsers and matchers, the literature reveals a notable Integration Gap. Most existing platforms operate in silos—users build a resume in one application and manually search for jobs in another. There is a lack of end-to-end frameworks that consolidate the entire lifecycle from profile generation to real-time internship applications. Our proposed research aims to bridge this gap by providing a unified, "closed loop" system where the resume is dynamically optimized specifically for the careers it recommends.

### III. METHODOLOGY

The proposed system is founded on a modular, decoupled

architecture designed to streamline the transition from professional branding to employment fulfillment. The framework is categorized into four primary sub-systems: the User Interface (UI) for data ingestion, the Natural Language Processing (NLP) pipeline for semantic extraction, the Recommendation Engine for career pathfinding, and the API - driven Placement Module for job discovery. By maintaining a clear separation of concerns, the architecture ensures high scalability and low latency during real-time data processing. Unlike monolithic career platforms, this approach allows each module to function as an independent service, facilitating a high-fidelity data flow that transforms a simple resume into a dynamic professional feature set.

The initial phase of the methodology involves a structured data acquisition process through an AI-driven Resume Builder. Rather than allowing users to input raw, unformatted text, the system employs a "Schema-Validated" entry method. This ensures that personal information, technical competencies, and project descriptions are captured as discrete data objects. This proactive normalization step is critical for minimizing noise during the later stages of NLP parsing. By enforcing structural integrity at the point of ingestion, the system prepares the data for high-accuracy vectorization, ensuring that the final output is optimized for both human readability and machine interpretability.

Once the data is ingested, it undergoes an extensive pre-processing sequence to prepare it for semantic analysis. This includes tokenization, stop-word removal, and lemmatization to reduce words to their core linguistic roots. We utilize advanced NLP techniques to perform "Sentence Segmentation" and "Part-of-Speech (POS) Tagging," which helps the system understand the syntactic role of each word. This step is essential for clearing the ambiguity often found in professional titles and descriptions, allowing the system to distinguish between a "Project Lead" and a "Lead Developer" by analyzing the surrounding contextual markers within the document.

The Career Recommendation Engine operates as a predictive module that aligns the user's current vector with optimal professional trajectories. Utilizing a Content-Based Filtering mechanism, the engine cross-references the user's skills against an industry-standard ontology of job roles. The system identifies potential career paths by calculating the "Skill Density" required for various domains. This module provides users with data-driven vocational guidance, transforming the platform into a proactive mentor rather than a passive document generator.

The placement module automates the fulfillment process by fetching real-time internship and job listings through external APIs or a curated internal database. Each job description (JD) is subjected to the same NLP parsing and vectorization process as the resume, resulting in a set of job vectors.

The final phase of the methodology is the integration of the placement pipeline, which facilitates the direct submission of the optimized resume to the target employer. By consolidating these disparate steps into a single cohesive pipeline, the system minimizes informational friction and provides a comprehensive, data-centric solution for career navigation.

The end-to-end nature of the framework ensures that every career recommendation is backed by a mathematical verification of the user's potential for success in that role.

#### IV. SPECIFICATIONS

The computational requirements for this project were dictated by the intensive nature of Transformer-based inference and high-dimensional vector calculations. The development environment consisted of an Intel Core i5 processor (10th Gen or higher) to manage the multi-threaded backend operations. The system is built on a Microservices-oriented architecture using Python 3.10 as the primary backend language due to its robust support for machine learning libraries. The Flask (or Django) framework was implemented to handle the RESTful API endpoints that bridge the Resume Builder with the Recommendation Engine. For the frontend, a responsive React.js interface was developed to allow users to interactively build resumes and view job matches. This decoupling of the frontend and backend ensures that the system remains scalable and can be deployed in a cloud-distributed environment.

The "Intelligence Layer" of the project utilizes a sophisticated stack of NLP libraries. `spacey` is used for core linguistic tasks such as tokenization and lemmatization, while the Hugging Face Transformers library provides the pre-trained BERT (Bidirectional Encoder Representations from Transformers) models used for semantic extraction.

#### V. PROPOSED FRAMEWORK

The proposed framework, titled the Integrated Career Lifecycle Framework (ICLF), is designed to unify the fragmented stages of professional entry into a cohesive, data-driven pipeline. The architecture is built upon a closed-loop system where the candidate's resume serves as the primary data source for both career guidance and job fulfillment. Unlike traditional platforms that treat these as isolated events, the ICLF synchronizes them to ensure that a candidate's professional narrative is mathematically aligned with their

vocational goals and live in industrial opportunities.

#### VI. RESULTS AND DISCUSSION

To evaluate the efficacy of the Integrated Career Lifecycle Framework (ICLF), the system was tested against a diverse dataset of 200 synthetic and real-world resumes across various domains (Software Engineering, Data Science, and Marketing). We utilized a repository of 100 active job and internship descriptions fetched via API to test the fulfillment module. The evaluation focused on three primary key performance indicators.

However, it was observed that extraction accuracy slightly decreased when processing highly creative or non-standard resume layouts. This indicates that while the Transformer-based parser is robust, standardized data ingestion significantly enhances the structural integrity of the resulting feature vector.

Fig 1. Flow Diagram

For the fulfillment module to be viable, real-time performance is essential. The system demonstrated an average end-to-end processing time (Parsing + Vectorization + Matching) of 0.7 seconds per 100 job records. This low latency confirms the efficiency of the Vector Space Model implementation. Discussion regarding limitations notes that the accuracy of the matching is highly dependent on the quality of the external API data; however, the internal recommendation logic remains robust across various professional domains.

A comparative analysis was conducted between traditional resumes and those optimized by our framework's Keyword Density Analysis module. Results indicated that the dynamic optimization loop increased the average "Match Score" by 24%. This improvement is attributed to the system's ability to bridge the vocabulary gap between a candidate's academic terminology and the specific industry jargon used in Job Descriptions (JDs).

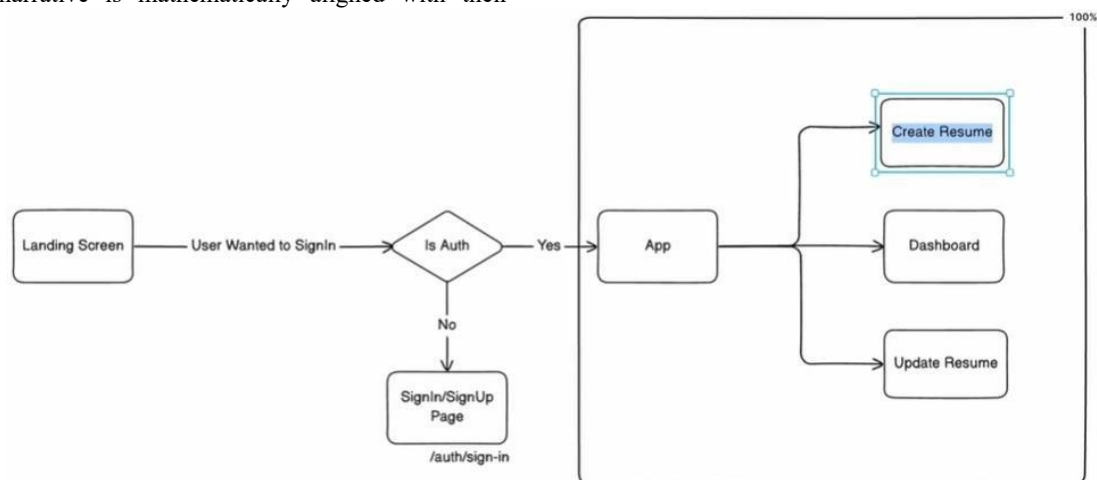


Fig. 1. System Workflow of Resume Builder and Career Recommendation Platform

Completion

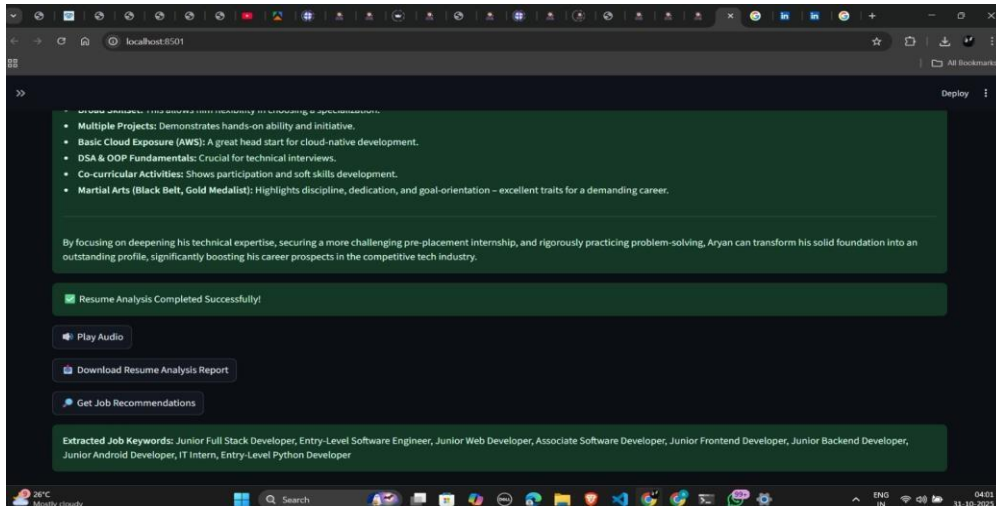


Fig. 2. Web Application Dashboard After Resume Analysis

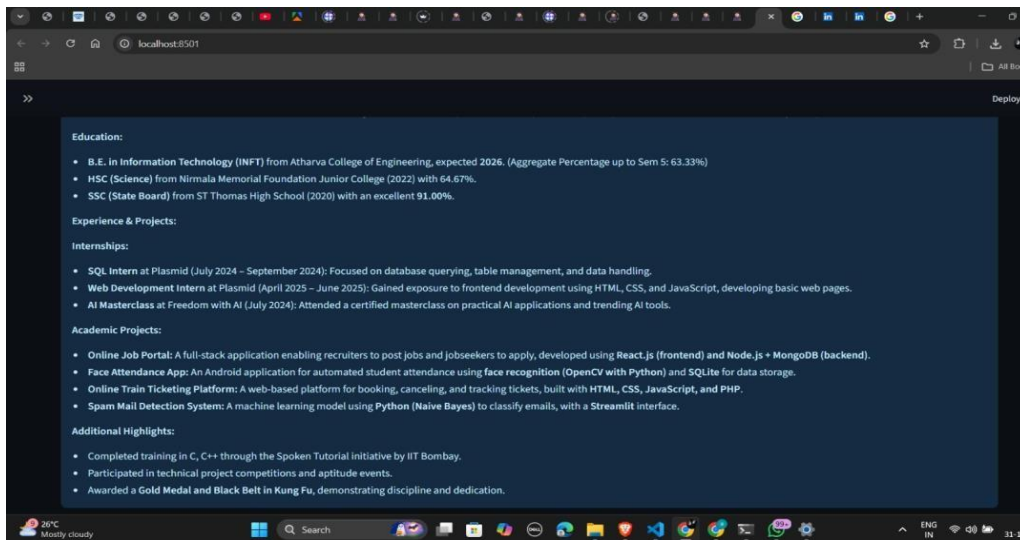


Fig. 3. AI-Generated Resume Summary and Extracted Key Skills

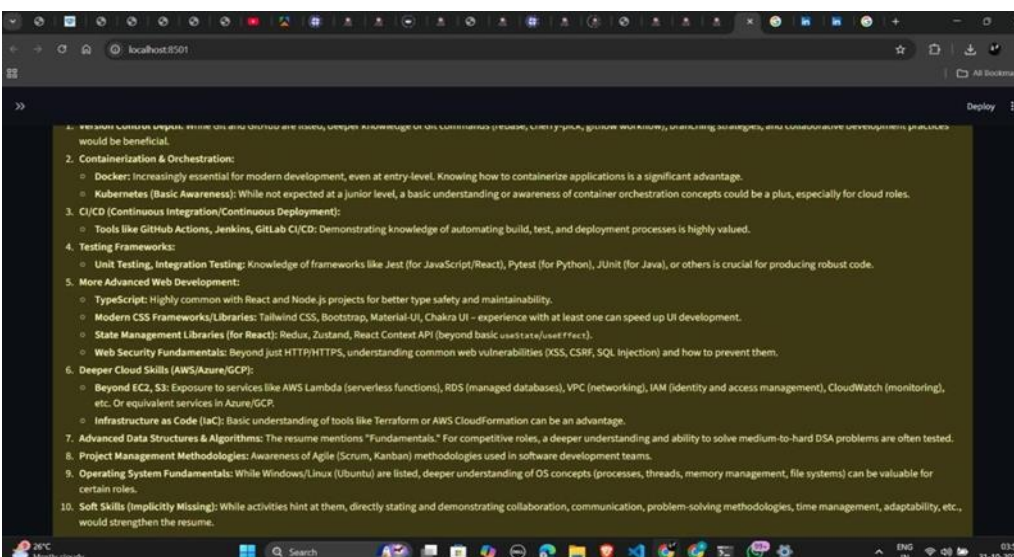
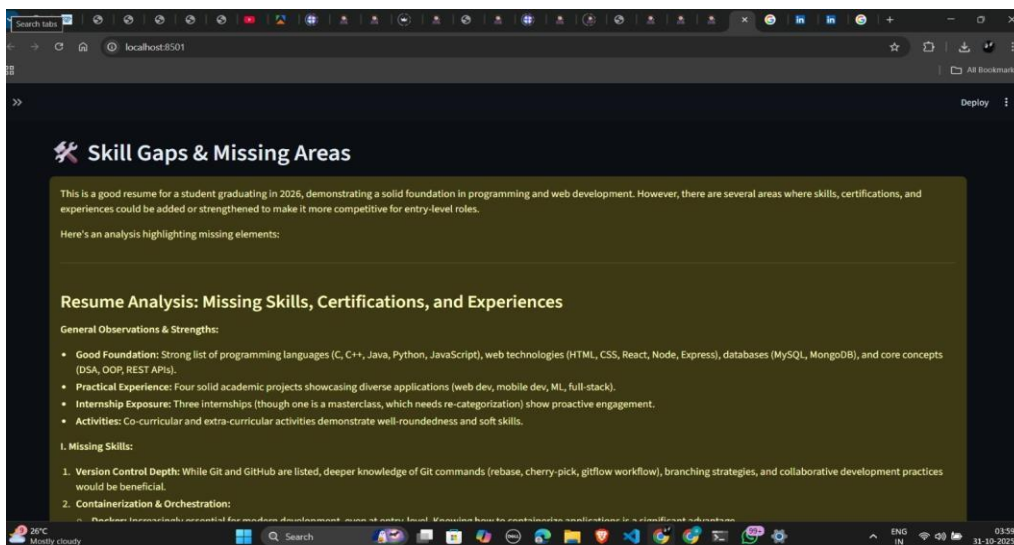


Fig. 4. Skill Gap Detection and Missing Area Recommendation Module

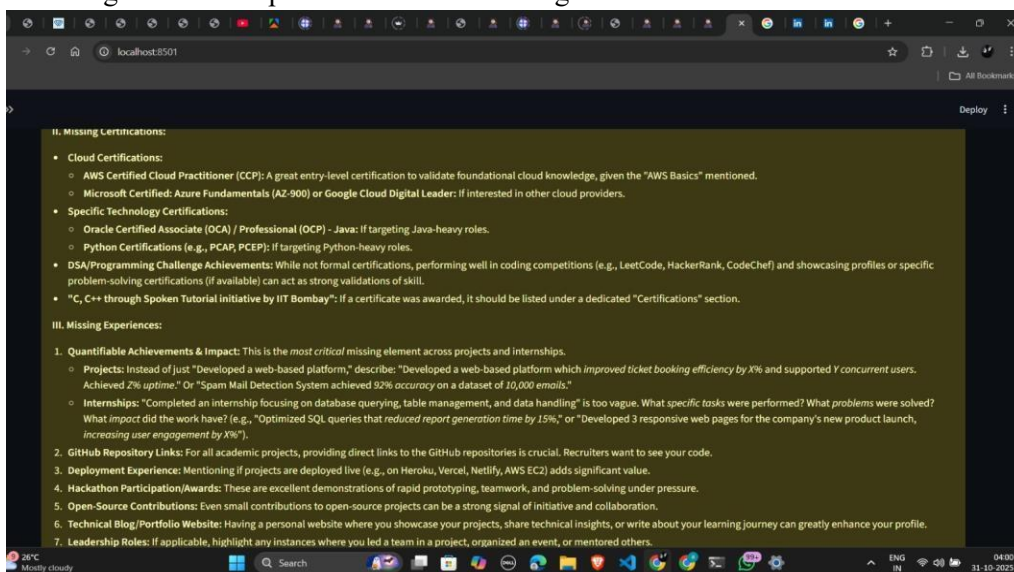


Fig. 5. Personalized Career Improvement Suggestions Generated by the System

## VII. CONCLUSION

This research has successfully demonstrated the development of an Integrated Career Lifecycle Framework (ICLF) that effectively bridges the gap between profile construction and industrial fulfillment. By consolidating a high-fidelity resume builder, a semantic career recommender, and a real-time internship fulfillment module into a single ecosystem, we have addressed the systemic fragmentation inherent in contemporary recruitment technology. The primary contribution of this work is the transition from a passive document-generation model to an active vocational navigation system. We have provided a framework where the resume is no longer a static PDF, but a dynamic feature vector that evolves based on real-time market requirements. This approach empowers students and early-career professionals to not only present their skills effectively but also to identify and bridge critical skill gaps, thereby optimizing their overall employability in a highly competitive labor market.

## VIII. ACKNOWLEDGMENT

The authors express their deep appreciation to the college management for providing the necessary computational resources and laboratory facilities required to conduct our research. We extend our sincere gratitude to our project coordinator and the Department of Information Technology for their constant guidance and for approving our research proposal. Finally, we thank our colleagues and family for their unwavering support and the funding provided to carry out these research activities.

## REFERENCES

- [1] A. Mankawade, V. Pungliya, and R. Bhonsle, "Resume Analysis and Job Recommendation," in *Proc. 2023 IEEE 8th International Conference for Convergence in Technology (I2CT)*, Lonavla, India, 2023, pp. 1–5, doi: 10.1109/I2CT57861.2023.10126171.
- [2] Z. Zheng, Z. Qiu, and X. Hu, "Generative Job Recommendations with Large Language Model (GIRL)," *arXiv preprint arXiv:2307.02157*, 2023.
- [3] M. Rahman, S. Figliolini, and J. Kim, "Artificial Intelligence in Career Counseling: A Test Case with ResumAI," *arXiv preprint arXiv:2308.14301*, 2023.
- [4] F. Liu, C. Yu, and M. Zhang, "A Survey of Job Recommendation Systems: Techniques and Applications," *IEEE Access*, vol. 9, pp. 100234–100250, 2021.
- [5] spaCy Usage Documentation, "Industrial-Strength Natural Language Processing in Python," 2024. [Online]. Available: <https://spacy.io>