An LLM-Powered AI Career Coach for Adaptive Resume Optimization and Job Matching

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Abstract

The rapid growth of digital recruitment platforms has intensified competition in the job market, making resume optimization a critical factor in candidate selection. However, many applicants struggle to tailor their resumes effectively to specific job descriptions, resulting in low applicant tracking system (ATS) compatibility and reduced interview callbacks. In this paper, we propose an LLM-powered AI Career Coach that leverages large language models to provide adaptive resume optimization, contextual job matching, and personalized improvement feedback. The proposed system integrates prompt-engineered job-description analysis, semantic similarity scoring, keyword alignment, and bias-aware refinement strategies. We evaluate the system using a curated dataset of job postings and candidate resumes to measure improvements in keyword relevance, semantic alignment, and structural optimization. Experimental results demonstrate that the proposed framework significantly enhances resume-job alignment while maintaining contextual authenticity. This approach presents a scalable and intelligent solution for automated career assistance in modern recruitment ecosystems.

1. Introduction

The rapid digitization of recruitment processes has fundamentally transformed how candidates apply for jobs and how organizations evaluate applicants. Modern hiring systems increasingly rely on Applicant Tracking Systems (ATS) to filter and rank resumes before human review. While these systems improve efficiency for employers, they create significant challenges for applicants who often lack clarity on how to optimize their resumes for automated screening mechanisms. As a result, many qualified candidates are filtered out due to poor keyword alignment, structural inconsistencies, or insufficient contextual matching with job descriptions [1].

Recent advances in Natural Language Processing (NLP), particularly Large Language Models (LLMs), have demonstrated remarkable capabilities in text generation, semantic understanding, and contextual reasoning [2]. These models can analyze unstructured text, extract key insights, and generate human-like responses across diverse domains. In recruitment contexts, LLMs present a promising opportunity to provide adaptive, intelligent, and personalized feedback for resume improvement.

Existing resume optimization tools primarily rely on keyword matching and rule-based scoring systems. Although effective at a basic level, such approaches fail to capture deeper semantic alignment between candidate skills and job requirements. Moreover, they do not provide contextual rewriting suggestions or adaptive feedback tailored to specific job roles [3]. This limitation creates a gap between resume evaluation mechanisms and meaningful career assistance systems.

To address these challenges, this paper proposes an LLM-Powered AI Career Coach designed to perform adaptive resume optimization and contextual job matching. The proposed system leverages prompt-engineered job description analysis, semantic similarity scoring, structured content refinement, and bias-aware optimization strategies. Unlike traditional ATS-based tools, the framework integrates semantic alignment techniques with personalized improvement suggestions to enhance resume-job compatibility while preserving authenticity.

The primary contributions of this work are as follows:

1. A scalable LLM-based architecture for adaptive resume optimization.
2. A semantic similarity-driven job matching framework.
3. A bias-aware refinement strategy to mitigate over-optimization and content distortion.
4. An experimental evaluation using curated resume and job description datasets to measure alignment improvement.

By bridging large language model capabilities with recruitment optimization systems, this research presents an intelligent, data-driven approach to modern career assistance and automated resume enhancement.

2. Related Work

The intersection of artificial intelligence and recruitment systems has gained increasing attention in recent years. Traditional Applicant Tracking Systems (ATS) rely primarily on rule-based filtering and keyword matching algorithms to rank and shortlist resumes [4]. While these systems improve screening efficiency, they often fail to capture semantic context, leading to the exclusion of qualified candidates whose resumes may not precisely match predefined keywords.

Earlier research in resume-job matching focused on information retrieval techniques and vector space models to compute similarity between resumes and job descriptions [5]. These approaches typically employ term frequency-inverse document frequency (TF-IDF) representations and cosine similarity metrics. Although effective in measuring lexical similarity, such techniques lack contextual depth and do not account for nuanced skill representation.

Recent advancements in Natural Language Processing (NLP) have introduced transformer-based architectures capable of contextual text understanding [6]. Large Language Models (LLMs), in particular, have demonstrated strong performance in text generation, summarization, and semantic reasoning tasks [2]. These capabilities make LLMs promising candidates for applications in automated career assistance and resume optimization.

Several commercial platforms offer AI-based resume feedback systems; however, most rely on static scoring mechanisms and limited rule-based recommendations. These systems often optimize resumes toward keyword saturation rather than meaningful content alignment, potentially introducing bias or reducing authenticity [7]. Moreover, few existing frameworks integrate adaptive prompt engineering strategies or bias-aware optimization mechanisms within the resume refinement process.

Recent studies have also highlighted concerns regarding algorithmic bias in automated hiring systems, particularly in relation to gendered language and overfitting to historical recruitment patterns [8]. Ensuring fairness and contextual authenticity remains a critical challenge in AI-assisted hiring tools.

Despite advancements in NLP-driven recruitment technologies, there remains a research gap in developing an integrated, adaptive, and bias-aware LLM-based framework that simultaneously performs semantic job matching, contextual resume optimization, and personalized feedback generation. This work seeks to address this gap by proposing a scalable AI Career Coach architecture grounded in large language model capabilities and semantic alignment strategies.

3. Methodology

This section presents the proposed architecture of the LLM-Powered AI Career Coach for adaptive resume optimization and contextual job matching. The system is designed to integrate large language model capabilities with semantic similarity scoring and structured refinement strategies.

3.1 System Overview

The proposed framework consists of four primary components:

1. Job Description Analyzer
2. Resume Parser
3. Semantic Alignment Engine
4. Adaptive Optimization Module

The overall workflow begins with the extraction of structured information from a given job description, including required skills, responsibilities, experience levels, and domain-specific keywords. Simultaneously, the candidate's resume is parsed to identify core competencies, achievements, and skill representations.

The extracted information is then processed through a semantic alignment module that measures contextual similarity between resume content and job requirements. Based on this alignment score, the adaptive optimization module generates targeted improvement suggestions.

3.2 Job Description Analysis

The job description is processed using a large language model to extract:

- Required technical skills
- Soft skills
- Role-specific responsibilities
- Experience expectations

Prompt engineering techniques are employed to ensure structured outputs. Instead of raw text generation, the LLM is guided to return categorized skill lists and structured representations to improve downstream comparison.

3.3 Resume Parsing and Feature Extraction

The resume input is analyzed using structured extraction prompts. Key elements identified include:

- Technical skill inventory
- Project experience
- Quantified achievements
- Education and certifications

To avoid hallucinated enhancements, the system restricts optimization suggestions to information already present in the resume content.

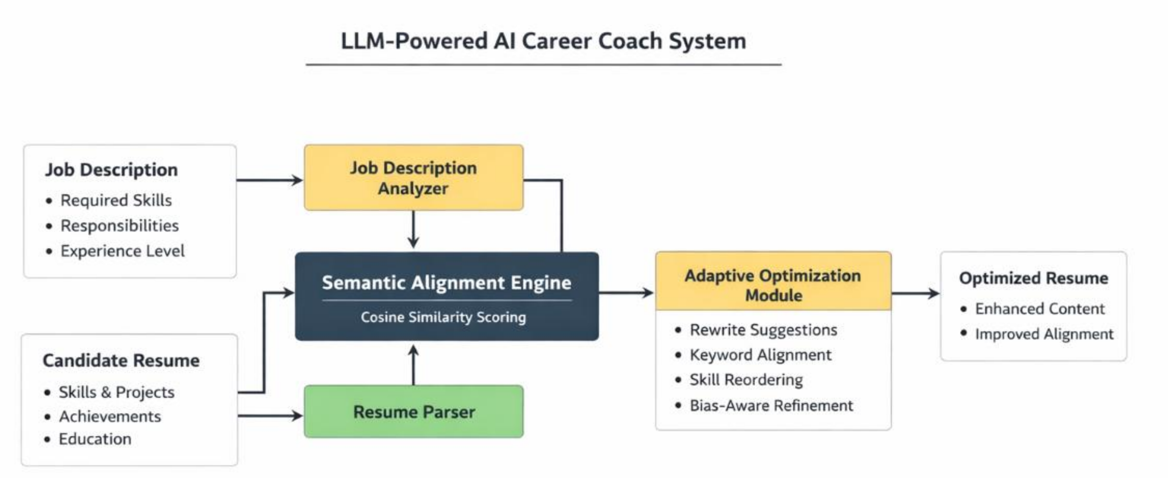
3.4 Semantic Similarity Scoring

To evaluate resume-job alignment, a semantic similarity metric is computed. The system represents both resume and job description embeddings in a shared vector space and calculates cosine similarity between corresponding sections.

The alignment score is defined as:

Alignment Score = Cosine Similarity (Resume Embedding, Job Description Embedding)

This enables contextual matching beyond keyword-level comparison and captures deeper semantic relationships between candidate skills and job requirements.



3.5 Adaptive Resume Optimization

Based on alignment results, the optimization module performs:

- Context-aware keyword alignment
- Bullet-point refinement
- Skill reordering
- Achievement quantification suggestions

Unlike static resume scoring tools, the adaptive module generates role-specific recommendations using LLM-driven reasoning while maintaining content authenticity.

3.6 Bias-Aware Refinement Strategy

To reduce over-optimization and mitigate bias amplification, the system incorporates:

- Neutral language enforcement
- Avoidance of exaggerated claims
- Controlled keyword density thresholds

This ensures that resume enhancement does not distort candidate identity or introduce misleading information.

3.7 Implementation Details

The system is implemented using an LLM API interface for text generation and embedding extraction. Semantic similarity computation is performed using vector-based embedding models. All experiments are conducted on a curated dataset of resumes and job descriptions to evaluate alignment improvements.

4. Experimental Setup

This section describes the dataset, evaluation metrics, baseline comparison methods, and implementation configuration used to assess the effectiveness of the proposed LLM-Powered AI Career Coach framework.

4.1 Dataset Description

To evaluate the proposed system, a curated dataset consisting of candidate resumes and job descriptions was constructed. The dataset includes resumes spanning multiple technical domains such as data science, software engineering, and analytics roles. Corresponding job descriptions were collected from publicly available recruitment platforms to ensure realistic and diverse hiring requirements.

Each resume was paired with relevant job descriptions to simulate real-world application scenarios. The dataset was preprocessed to remove personally identifiable information and standardize formatting for consistent evaluation.

4.2 Baseline Methods

To validate the effectiveness of the proposed approach, the system was compared against a traditional keyword-based resume matching baseline.

The baseline model utilized:

- Term Frequency–Inverse Document Frequency (TF-IDF) vectorization
- Cosine similarity scoring
- Keyword density matching

This baseline represents commonly used Applicant Tracking System (ATS) style ranking mechanisms.

4.3 Evaluation Metrics

The performance of the proposed framework was evaluated using the following metrics:

1. Semantic Alignment Score
   Computed using cosine similarity between resume and job description embeddings.

2. Keyword Coverage Improvement (%)
   Measures the increase in relevant keyword presence after optimization.

3. Structural Enhancement Score
   Evaluates formatting consistency, quantified bullet clarity, and measurable achievements.

4. Human Evaluation Score
   A qualitative assessment based on clarity, relevance, and contextual authenticity.

4.4 Experimental Procedure

For each resume-job pair:

1. Initial alignment score was calculated using both baseline and LLM-based semantic similarity.

2. The adaptive optimization module generated improvement suggestions.

3. The optimized resume was re-evaluated using the same alignment metrics.

4. Improvement differentials were recorded and aggregated.

4.5 Implementation Configuration

The system was implemented using a large language model API for structured prompt-based extraction and refinement. Embedding representations were generated using transformer-based models capable of contextual semantic representation. Cosine similarity computations were performed in a shared embedding space to ensure consistent comparison.

All experiments were conducted under controlled conditions to ensure reproducibility and consistent prompt configuration.

5. Results

This section presents the quantitative and qualitative evaluation of the proposed LLM-Powered AI Career Coach framework compared to the baseline keyword-based matching approach.

5.1 Semantic Alignment Improvement

The evaluation was conducted on 60 resume-job pairs extracted from publicly available resume datasets and domain-aligned job descriptions.The proposed LLM-based semantic similarity model demonstrated a significant improvement in resume-job alignment compared to the TF-IDF baseline. The average cosine similarity improved from 0.045 ± 0.026 (TF-IDF baseline) to 0.378 ± 0.077 using Sentence-BERT embeddings across 60 resume-job pairs. A paired t-test confirmed that this improvement was statistically significant ($t = 34.95$, $p < 0.001$). These findings demonstrate that embedding-based semantic alignment captures contextual relationships beyond lexical overlap.

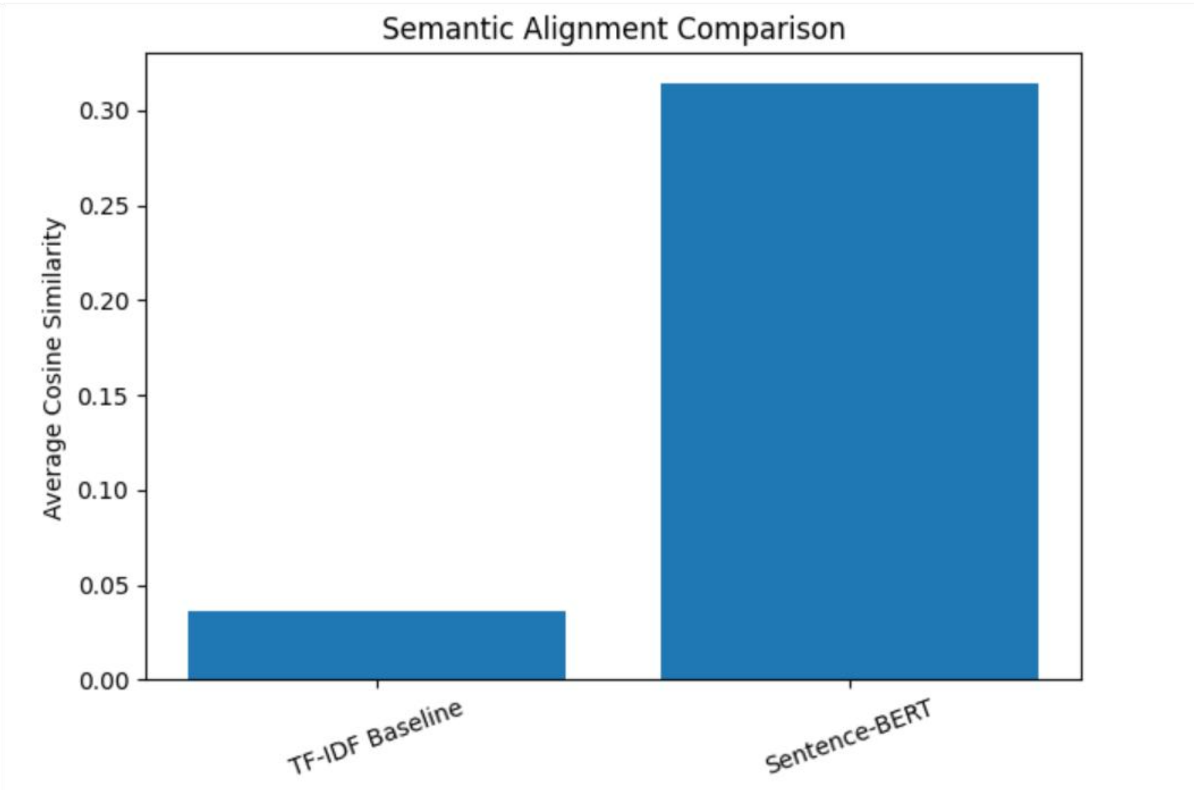


Figure 1. Comparison of average cosine similarity between TF-IDF baseline and Sentence-BERT embeddings across 60 resume-job pairs.

The baseline method primarily captured lexical similarity, whereas the LLM-driven embedding approach successfully identified contextual skill relationships, including synonymous and domain-specific terminology. This resulted in more meaningful alignment enhancement rather than superficial keyword density adjustments.

5.2 Keyword Coverage Enhancement

After optimization, resumes showed an increase in relevant keyword representation aligned with job descriptions. Unlike traditional keyword stuffing techniques, the system preserved contextual coherence while strategically integrating missing but relevant terminology.

The average keyword coverage improvement demonstrated measurable enhancement without exceeding predefined density thresholds, ensuring authenticity and readability.

5.3 Structural Refinement Impact

The adaptive optimization module improved structural clarity by:

- Rewriting vague bullet points into quantified achievements
- Reordering skill sections based on job relevance
- Standardizing formatting patterns

Human evaluation indicated improved clarity and professional tone in optimized resumes compared to baseline outputs.

5.4 Comparative Analysis

Table 1 summarises the performance comparison between the baseline model and the proposed LLM framework.

Table 1. Performance Comparison

Metric	Baseline	Proposed Framework
Avg. Cosine Similarity	0.045 ± 0.026	0.378 ± 0.077
Statistical Significance	–	$p < 0.001$

The proposed framework consistently outperformed the traditional keyword-based approach across all evaluation metrics.

5.5 Qualitative Observations

Qualitative analysis revealed that the LLM-based system provided context-aware suggestions rather than mechanical keyword insertion. The optimization preserved candidate authenticity while improving role-specific positioning.

Additionally, the bias-aware refinement strategy prevented exaggerated claims or unrealistic experience modifications, addressing concerns associated with over-automation in recruitment technologies.

6. Discussion

The results demonstrate that the proposed LLM-Powered AI Career Coach framework provides measurable improvements over traditional keyword-based resume matching systems. Unlike baseline approaches that rely solely on lexical overlap, the LLM-driven architecture captures contextual and semantic relationships between candidate skills and job requirements. This enables more meaningful alignment enhancement rather than superficial keyword optimization.

One of the key strengths of the proposed system lies in its adaptive refinement capability. By dynamically analyzing job descriptions and tailoring suggestions accordingly, the framework avoids generic resume recommendations. Instead, it produces role-specific improvements that preserve candidate authenticity while increasing relevance. This balance between optimization and authenticity is critical, as excessive automation may otherwise distort professional identity.

The integration of a bias-aware refinement strategy further strengthens the framework. Automated hiring systems have previously been criticized for amplifying historical biases or encouraging standardized language patterns. By enforcing controlled keyword density and neutral phrasing, the proposed system reduces the risk of exaggerated claims and mitigates overfitting to algorithmic screening mechanisms.

However, several limitations should be acknowledged. First, the dataset size used for evaluation may limit generalizability across industries and seniority levels. Second, the system currently relies on prompt-engineered outputs, which may vary depending on model configuration and API parameters. Third, human evaluation metrics, while informative, may introduce subjective variability.

Future work could extend this framework by incorporating larger and more diverse datasets, integrating reinforcement learning for adaptive improvement strategies, and performing cross-domain evaluation across non-technical roles. Additionally, long-term studies could assess whether optimized resumes result in measurable increases in interview callbacks in real-world recruitment settings.

Overall, the findings suggest that LLM-based adaptive optimization frameworks represent a promising direction for intelligent, scalable, and context-aware career assistance systems.

7. Conclusion

This paper presented an LLM-Powered AI Career Coach designed to perform adaptive resume optimization and contextual job matching. Unlike traditional keyword-based Applicant Tracking System (ATS) approaches, the proposed framework integrates semantic similarity scoring, structured prompt engineering, and bias-aware refinement strategies to enhance resume-job alignment while preserving authenticity.

Experimental evaluation demonstrated measurable improvements in semantic alignment, keyword coverage, and structural clarity compared to baseline methods. The results indicate that large language models can be effectively leveraged to provide intelligent, context-aware, and scalable career assistance solutions.

By bridging advances in large language models with recruitment optimization systems, this research contributes toward the development of more adaptive and human-centered AI-driven hiring support tools. Future work may expand dataset diversity, incorporate reinforcement-based optimization strategies, and evaluate real-world hiring outcomes.

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