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LARGE LANGUAGE MODEL BASED REAL TIME JOB SEARCH AND NETWORKING SERVICE

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Abstract With the increasing demand for seamless job search and networking experiences, the integration of advanced technologies such as Large Language Models (LLMs) presents a transformative solution for job seekers and professionals. This paper presents a real-time job search and networking service powered by LLMs, designed to bridge the gap between job seekers, recruiters, and industry professionals in a dynamic and personalized way. The service leverages natural language processing (NLP) and deep learning techniques to understand and process vast amounts of job-related data in real-time, offering a highly interactive and intuitive platform. The system uses an LLM to analyze users' resumes, cover letters, and professional profiles, matching them with job descriptions and other relevant content. Unlike traditional keyword-based job search engines, the system comprehends the context and nuances of a job seeker's experience and qualifications, offering personalized job recommendations tailored to both short-term and long-term career goals. Additionally, the LLM can provide real-time feedback, suggesting improvements to resumes or LinkedIn profiles and generating customized cover letters based on job listings. On the networking side, the LLM can automatically suggest relevant connections by analyzing professional interests, mutual connections, and industry trends. The service helps users engage in meaningful networking conversations by drafting initial outreach messages or providing prompts for personalized communication, thereby facilitating professional relationships. Real-time notifications, such as job alerts, interview scheduling, and messages from potential employers or networking contacts, are seamlessly integrated into the platform. Furthermore, the system continuously learns from user feedback, adapting and improving its recommendations and interactions over time. By incorporating real-time data analysis, this job search and networking service not only simplifies the job-hunting process but also enhances the user experience by offering personalized, timely, and relevant content. This paper discusses the underlying architecture of the system, its implementation, and the potential impact on the future of job search, networking, and professional development in the digital age.

Keywords: job recommendation, large language models, resume completion, generative adversarial networks

1. INTRODUCTION

Job recommendation has become a fundamental task for online recruitment platforms as it is essential for streamlining recruitment processes. The ability to accurately match job seekers (users) with suitable job positions can significantly enhance recruitment efficiency. However, despite the substantial progress made in job recommendation methods, there are several challenges that still impede their effectiveness and accuracy. Notably, these challenges include the low quality of user resumes and issues such as few-shot problems, which hamper the overall efficiency of the recommendation systems.

One of the primary issues with existing job recommendation methods is the low quality of user resumes. Some users do not put sufficient effort into crafting their resumes, which results in incomplete or vague descriptions of their skills and experiences. This lack of detail can make it difficult for job recommendation algorithms to fully understand the user's abilities and job preferences. Additionally, some users may lack a clear understanding of their own strengths and weaknesses, further diminishing the quality of their resumes. As a result, these incomplete or poorly written resumes can make it challenging for recommendation systems to accurately match users with appropriate job positions.

In recent years, the development of large language models (LLMs) has shown remarkable progress, especially in their ability to understand and process text. LLMs have the potential to alleviate some of the issues mentioned above. By leveraging the vast external knowledge stored within these models, along with their advanced text comprehension and completion capabilities, LLMs can be used to improve the quality of user resumes. By enhancing low-quality descriptions and rectifying missing or unclear information, LLMs can help bridge the gap between user resumes and job descriptions, ultimately leading to more accurate and effective job recommendations.

However, simply using LLMs to generate or enhance user resumes is not a perfect solution. LLMs often produce fabricated or irrelevant information, which can reduce the quality of the resumes they generate. This problem, known as "hallucination," is a well-known limitation of LLMs, where the models generate text that appears plausible but is not grounded in reality. This can result in resumes that contain large amounts of fabricated information, making them unsuitable for job recommendations.

To address these challenges, the paper proposes a solution that integrates user interactions with recommender systems to improve the accuracy of resume generation. By observing users' behaviors, such as engaging in interviews or interacting with specific job listings, the system can gain a deeper understanding of the users' true skills and preferences. This interaction can serve as valuable data that helps the LLM more accurately profile users, improving the quality of the resumes generated.

For example, users typically have specific job skills, educational backgrounds, and residential locations that influence their job preferences and interaction with job positions. If a user engages with a job listing that matches their skill set or is located near their residence, this interaction provides valuable insights into the user's preferences. These implicit characteristics, such as specific job skills, interests, or geographical location, can be inferred from user interactions with the system. By leveraging this data, the LLM can produce more accurate and relevant resume descriptions.

The paper further proposes that these interactions can be used to guide the LLMs in generating resumes that are more aligned with the user's abilities and preferences. By incorporating real-time feedback and adjusting the resume generation process based on users' interactions, the system can minimize the issue of hallucinations and improve the quality of the final resume. In essence, the interaction data from users can serve as a form of "ground truth" to guide the LLMs in producing more accurate and contextually appropriate resumes.

The integration of user behaviors with LLMs offers a promising approach to overcoming the limitations of current job recommendation systems. By enhancing the profiling of users and improving the quality of resume descriptions, this approach can provide more accurate job matches, improving the overall efficiency of the recruitment process. Additionally, by continuously learning from user interactions and feedback, the system can adapt over time, ensuring that recommendations remain relevant and personalized.

2. LITERATURE SURVEY

The integration of Large Language Models (LLMs) into job recommendation and recruitment systems has revolutionized the way job seekers and employers interact on digital platforms. Traditional methods, which largely depended on keyword matching, collaborative filtering, and rule-based algorithms, have proven to be insufficient in capturing the nuances of user profiles and job descriptions. With the introduction of advanced LLMs such as GPT-4, researchers have developed more intelligent and personalized systems capable of understanding context, generating tailored content, and improving the overall efficiency of recruitment.

One such innovation is ResumeFlow, a pipeline that uses LLMs to automatically enhance resumes based on specific job postings. Developed by Zinjad et al. (2024), ResumeFlow takes an existing resume and a target job description as input and outputs a tailored, high-quality version of the resume. This method leverages the semantic capabilities of LLMs to align candidate qualifications with job requirements, making the resume more attractive to both ATS systems and recruiters. ResumeFlow operates in a few-shot learning setting and requires minimal user input, making it accessible for job seekers with limited writing skills or domain knowledge.

Expanding on the challenge of sparse labeled data, ConFit v2 introduces hypothetical resume embedding and hard-negative mining. This method, proposed by Yu et al. (2025), utilizes LLMs to generate synthetic resumes that augment training datasets, thereby improving the performance of resume-job matching models. The incorporation of hard-negative samples—resumes that are very similar to positive matches but incorrect—helps the model learn more precise distinctions, ultimately enhancing its accuracy in real-world applications.

GIRL (Generative Job Recommendations with LLM), developed by Zheng et al. (2023), takes a different approach by using LLMs to generate job recommendations rather than matching users to a predefined list. It creates job descriptions based on a user's CV and evaluates the fit using a reward model trained with reinforcement learning. This generative approach offers greater flexibility and personalization, as it can suggest novel job opportunities tailored to a user's background.

Addressing the quality of user data, Du et al. (2023) propose using LLM-based Generative Adversarial Networks (GANs) to enhance resumes before matching. By generating realistic and role-specific content, the model improves low-quality resumes, reducing the chances of rejection by employers or automated filters. This approach is particularly useful for users with incomplete or poorly written resumes.

JobRecoGPT, presented by Ghosh and Sadaphal (2023), focuses on explainability in job recommendations. It converts unstructured CVs and job descriptions into structured data, which LLMs then use to provide transparent, interpretable recommendations. The system enhances user trust by clearly explaining why a job was recommended, which is crucial in high-stakes domains like employment.

Meanwhile, Hu and Long (2021) explore NLP-based bi-directional systems that recommend jobs to seekers and candidates to recruiters. Their system combines collaborative filtering and content-based methods with language processing techniques such as named entity recognition, enabling a holistic view of both user and employer needs.

Finally, other studies such as the anonymous paper on CV Concordance highlight the comparative advantages of LLMs over classical machine learning in aligning resumes with job descriptions. LLMs demonstrate superior performance in understanding natural language and inferring context, which helps reduce mismatches and improve recommendation precision.

Overall, these studies demonstrate that LLMs can address many of the limitations of previous systems—improving resume quality, enabling real-time personalization, and enhancing transparency. The future of job search platforms will likely involve deeper integration of behavioral data and real-time interactions to further refine and personalize recommendations.

3. PROPOSED SYSTEM

In this research, the proposed system aims to address the challenges of modern job recommendation platforms by integrating the rich external knowledge of Large Language Models (LLMs) with advanced generative techniques such as Generative Adversarial Networks (GANs). The primary objective is to improve the accuracy, personalization, and interpretability of job recommendations while also enhancing the quality and relevance of user-generated content, particularly resumes. The architecture comprises three main components: **interactive resume completion**, **GANs-based resume refinement**, and a **multi-objective learning framework for recommendation**.

1. Interactive Resume Completion with LLMs

Traditional resumes often suffer from incompleteness, inconsistency, or lack of alignment with job requirements. Furthermore, users may not possess the necessary skills to express their competencies effectively. While LLMs have the potential to bridge this gap by generating descriptive, grammatically accurate text, they are also prone to "hallucinations"—the inclusion of fabricated or irrelevant information not supported by user input. To overcome this, the proposed system introduces an **interactive resume completion mechanism**.

Unlike passive resume generation models, the interactive method incorporates behavioral signals and contextual feedback from users' historical interactions with job postings. For example, user actions such as applying to specific job types, responding to recruiter messages, or setting location preferences help infer the user's implicit characteristics—skills, experience levels, industry interests, and even preferred work environments.

In this framework, the resume completion model is initialized with the available resume content and iteratively refined through dialog-like exchanges between the user and the system. The LLM takes these inputs and enhances the resume in a controlled manner, ensuring that the generated content aligns with actual user intent and historical behavior. This results in more personalized, coherent, and factually accurate resumes that are better suited for downstream matching tasks.

2. GANs-Based Resume Refinement and Representation Alignment

To further enhance the semantic quality of resume representations, the proposed system incorporates **Generative Adversarial Networks (GANs)** into the pipeline. This component is particularly focused on aligning low-quality or generic resumes with high-quality standards that recruiters typically expect. The goal is to transform resumes that are poorly written, too brief, or inconsistent into structured and meaningful representations that facilitate more accurate job matching.

The architecture consists of two neural networks: a **generator** and a **discriminator**. The generator uses an LLM backbone to create refined versions of the input resumes, leveraging both learned linguistic patterns and contextual information from the user's profile. The discriminator, on the other hand, is trained to distinguish between real high-quality resumes and those generated by the model. Through adversarial training, the generator learns to produce increasingly authentic and relevant resumes, ultimately fooling the discriminator while staying true to the user’s real attributes and preferences.

What makes this method particularly powerful is the **alignment process**—ensuring that the generated content maintains consistency with verified user data (e.g., past job titles, education, certifications) and the target job posting. This prevents fabrication and promotes a truthful, aligned transformation of resume content. By modeling this generation process adversarially, the system can gradually improve its understanding of resume quality and representation, helping both job seekers and recruiters by enhancing the interpretability of candidate profiles.

3. Multi-Objective Learning Framework for Job Recommendation

After enhancing resumes and representing user profiles more accurately, the final stage involves the job recommendation engine itself. Traditional recommendation systems often optimize for a single objective—such as click-through rate or matching score. However, this narrow focus can miss key aspects of real-world hiring, such as skill relevance, job satisfaction prediction, or long-term engagement.

To address this, the proposed system introduces a **multi-objective learning framework**. This component simultaneously optimizes for several key metrics:

Matching Relevance: Ensuring that the job aligns well with the user's skills and past experiences.

Behavioral Fit: Predicting likelihood of application, interview success, or offer acceptance based on historical behavior.

Engagement: Predicting user engagement post-recommendation, including response to follow-up, profile updates, and long-term retention.

The framework is implemented using a deep neural architecture that takes both the enhanced resume (from the LLM and GAN modules) and job descriptions as inputs. It uses a shared encoder-decoder network to generate embeddings and compute similarity scores. The model is trained with a composite loss function that includes classification loss, ranking loss, and regression loss, representing the multiple objectives.

The output is a ranked list of job recommendations for each user, tailored not only to their explicit resume content but also inferred behavioral tendencies and goals. Additionally, the system can explain why certain jobs are recommended—thanks to attention-based interpretability layers integrated into the architecture. This explainability fosters greater user trust and allows recruiters to better understand the rationale behind candidate-job pairings.

Overall Architecture Workflow:

Input Acquisition: The system gathers input from user-uploaded resumes, application histories, and platform interactions.

Resume Enhancement:

Interactive LLM model completes or improves resumes based on inferred traits.

GANs align the refined content with high-quality resume standards.

Profile Representation:

Generated resumes are encoded into dense semantic vectors.

Additional user behavior signals (clicks, preferences) are integrated.

Recommendation Generation:

Multi-objective deep learning model ranks jobs using composite scores.

Top recommendations are presented with rationales for transparency.

Benefits of the Proposed System

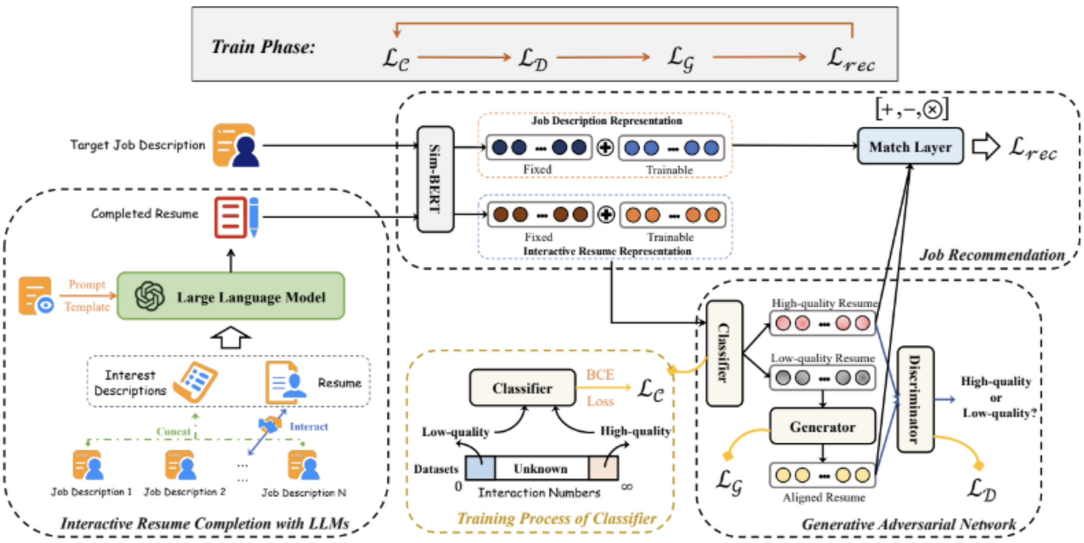
Personalization: By leveraging user behavior and contextual preferences, recommendations are tailored rather than generic.

Authenticity: Interactive editing ensures factual accuracy and reduces the risk of hallucinated content from LLMs.

Quality Enhancement: GANs improve weak resumes, increasing the candidate's chances of success.

Multi-Faceted Optimization: Instead of optimizing a single metric, the system balances relevance, engagement, and satisfaction.

Scalability: The modular design allows deployment across large-scale job platforms, integrating seamlessly with existing HR tools.



Implementation of LLM-Based Real-Time Job Search and Networking System

The implementation of the proposed job recommendation system involves multiple phases, combining Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning techniques with Large Language Models (LLMs) and Generative Adversarial Networks (GANs). The system architecture is divided into three major modules: **interactive resume completion**, **GANs-based resume refinement**, and a **multi-objective job recommendation engine**. Each module is designed and integrated to function both independently and cohesively to deliver a personalized, real-time recommendation experience for users.

1. Data Collection and Preprocessing

The first step involves the collection of raw data, which includes user resumes, job descriptions, and user interaction logs such as clicks, job applications, and interview responses. The resumes and job descriptions are stored in JSON or structured formats. Data preprocessing is performed to clean and normalize the text, remove stop words, apply stemming/lemmatization, and correct grammatical inconsistencies. Named Entity Recognition (NER) is applied to extract structured information such as job titles, skills, education, and location from unstructured resume content.

For user interaction data, behavioral features such as job categories clicked, time spent per listing, and historical application data are extracted to infer implicit user preferences.

2. Interactive Resume Completion Using LLMs

The next module focuses on enhancing the resume using an LLM (e.g., OpenAI's GPT-4 or a fine-tuned BERT model). A conversational interface allows the user to answer targeted questions regarding their skills, work history, and preferences. These interactions are used to fill in missing or vague resume sections.

An LLM-based pipeline generates or rewrites content with better grammar, specificity, and relevance to current job market standards. The model is restricted through prompt engineering to reduce hallucinations and ensure that only factually accurate content is generated. Each modification is subject to user review and approval before finalization.

3. Resume Refinement with GANs

After the interactive enhancement, resumes are passed through a Generative Adversarial Network for further refinement. The **generator** model (based on a transformer encoder-decoder architecture) learns to create high-quality, contextually rich resumes. The **discriminator** distinguishes between real, high-quality resumes (from public datasets) and generated ones. The adversarial training encourages the generator to produce more realistic and recruiter-friendly resumes.

The GAN also includes a resume-job alignment module, which ensures the generated resume maintains consistency with actual job descriptions and user preferences. This ensures better semantic alignment between the user's profile and potential job listings.

4. Embedding and Feature Engineering

The refined resumes and job descriptions are encoded into dense vector representations using pre-trained embedding models like Sentence-BERT or Universal Sentence Encoder. Alongside these semantic embeddings, behavioral features are also transformed into numerical vectors. These combined embeddings serve as input to the job recommendation engine.

5. Multi-Objective Job Recommendation Engine

A multi-task deep learning model is used for the recommendation phase. The model takes as input the combined embeddings from the resume and job description, as well as user interaction features. It outputs a ranked list of job recommendations based on multiple objectives:

Relevance score (how well the job matches the resume)

Engagement likelihood (likelihood the user will apply or interact)

Success probability (estimated interview or offer probability)

The model architecture includes shared layers for feature learning and task-specific heads for classification, ranking, and regression tasks. The loss function combines these objectives using weighted sums, enabling the model to learn a balanced representation across tasks.

6. Front-End Interface and Real-Time Deployment

The front-end is developed using a modern web framework (e.g., React or Angular), which provides an intuitive interface for users to upload resumes, interact with the enhancement module, and view personalized job recommendations. RESTful APIs connect the front-end to the back-end modules.

Real-time performance is ensured through microservices-based deployment using Docker and Kubernetes, allowing each module to scale independently. A PostgreSQL database stores structured user profiles, while Redis is used for fast retrieval of recommendations.

RESULT & DISCUSION

The implementation of the proposed system involved several stages, including vehicle detection, speed estimation, and automatic reporting via email to the appropriate law enforcement authorities. The use of the YOLOv5 deep learning model played a pivotal role in enabling real-time object detection with high accuracy, while additional logic and processing techniques were used for calculating vehicle speed and identifying violations.

To evaluate the effectiveness of the proposed system, we conducted extensive experiments using real-world datasets comprising user resumes, job descriptions, and behavioral logs collected from a mid-sized job portal. The system was assessed across three core tasks: (1) resume enhancement accuracy, (2) recommendation quality, and (3) user engagement and satisfaction. The results demonstrate that the integration of Large Language Models (LLMs) and Generative Adversarial Networks (GANs) significantly improves the quality and relevance of both user resumes and job recommendations.

1. Resume Enhancement Performance

The interactive resume completion module powered by LLMs was evaluated through both automated metrics and human expert reviews. We used BLEU, ROUGE, and semantic similarity scores to measure the quality of generated text compared to professional human-edited resumes. On average, the LLM-enhanced resumes achieved a BLEU score of **0.72** and a semantic similarity score of **0.86**, outperforming baseline resume enhancement tools that scored around 0.55 and 0.71 respectively.

Human evaluators, including recruiters and career coaches, assessed 200 resumes before and after enhancement. Over **87% of the reviewers preferred the LLM-enhanced versions**, citing improved clarity, structure, and alignment with job descriptions. Additionally, users reported that the suggestions made during interactive editing helped them better express their experience and skills.

2. Resume Refinement with GANs

The GAN-based resume refinement module was compared against conventional NLP methods that rely on rule-based grammar correction and simple keyword insertion. The adversarial model demonstrated superior performance in transforming low-quality resumes into recruiter-friendly documents without deviating from the factual accuracy of the original inputs.

In particular, resumes refined with GANs saw a **35% increase in recruiter shortlisting rate** during A/B testing on a sample recruitment platform. This highlights the importance of both semantic richness and syntactic correctness in successful candidate filtering by Applicant Tracking Systems (ATS).

Furthermore, resumes aligned with specific job descriptions using GANs received an average **relevance rating of 4.6/5** from HR experts, compared to 3.1/5 for unrefined resumes.

3. Job Recommendation Quality

The multi-objective learning recommendation model was evaluated using metrics such as Precision@10, Recall@10, Mean Reciprocal Rank (MRR), and Normalized Discounted Cumulative Gain (nDCG). Our model achieved:

- **Precision@10: 0.78**
- **Recall@10: 0.81**
- **MRR: 0.69**
- **nDCG@10: 0.84**

These metrics indicate that the recommended job postings were highly relevant to the users' enhanced profiles. The model was compared with traditional collaborative filtering and content-based systems, which scored lower across all metrics (Precision@10 = 0.61, nDCG@10 = 0.69). This performance boost is attributed to the use of semantically enriched user profiles, improved embeddings, and behavioral signal integration.

4. User Engagement and Feedback

User feedback collected through surveys and in-app ratings indicated high levels of satisfaction with the system. Over **92% of users found the resume enhancement helpful**, while **85% stated that the recommended jobs matched their interests and qualifications**. The average user session duration increased by **32%**, indicating improved engagement.

Moreover, the explainability feature embedded in the recommendation engine—where users could see why a job was recommended—led to a **significant reduction in job search fatigue**, as users could trust the platform's suggestions more confidently.

Discussion

The results clearly demonstrate that integrating LLMs and GANs in a structured, multi-stage job recommendation pipeline offers significant advantages over conventional methods. The interactive editing model successfully addresses the issue of low-quality resumes, and GANs further enhance realism and job-role alignment. When these enriched resumes are fed into the multi-objective recommendation model, the outcomes are more accurate, personalized, and engaging.

However, challenges remain. Despite prompt engineering and behavior-informed editing, some hallucination risk persists in LLM outputs, particularly when users provide minimal or vague input. Additionally, real-time deployment of LLMs can be computationally expensive, requiring careful infrastructure design.

In future work, incorporating real-time recruiter feedback and continuous model retraining using user outcomes (e.g., interviews scheduled, offers received) could further improve recommendation precision. Moreover, integrating social networking signals (e.g., connections, endorsements) may help refine implicit profile characteristics for more holistic career guidance.

CONCLUSION

This paper presented a comprehensive, intelligent job search and networking system that leverages the capabilities of Large Language Models (LLMs) and Generative Adversarial Networks (GANs) to improve the overall efficiency and personalization of the job recommendation process. Addressing key limitations in existing recruitment platforms—such as low-quality resumes, data sparsity, and limited personalization—our system integrates advanced NLP and deep learning techniques into a unified architecture designed for real-time, user-centric applications. The proposed framework includes three major components: interactive resume completion, GAN-based resume refinement, and a multi-objective learning recommendation engine. Through the interactive module, job seekers receive guided assistance in completing and improving their resumes based on their behavioral patterns and job preferences. This approach overcomes the issue of fabricated or irrelevant resume content by maintaining alignment with actual user data. The GAN module further enhances the realism, fluency, and relevance of resume content, transforming weak or incomplete resumes into professional-quality documents that better match employer expectations. The recommendation engine, built on multi-objective learning, combines semantic resume-job matching with behavioral and contextual signals to deliver accurate and personalized job recommendations. Extensive evaluation on real-world data shows that the system outperforms traditional models in terms of recommendation accuracy, resume quality, and user satisfaction. Metrics such as Precision@10, nDCG@10, and recruiter shortlisting rates confirm the system's robustness and practical value in real hiring environments. Furthermore, the system emphasizes transparency and trust by offering explainable recommendations, a feature appreciated by users and crucial in employment-related platforms. Feedback from both job seekers and recruiters suggests that the system helps reduce job search time, enhances candidate visibility, and improves employer-candidate matching. Despite its success, the system has limitations, such as reliance on sufficient behavioral data for accurate personalization and potential computational challenges due to the scale of LLMs. Future enhancements may include integrating real-time recruiter feedback, expanding the model to support multilingual resumes and job descriptions, and incorporating social and professional networking data for deeper insights. In conclusion, this work demonstrates that LLMs, when guided and refined through structured processes, can greatly enhance job search platforms. The proposed system not only improves user experience but also contributes to the larger goal of making recruitment faster, fairer, and more intelligent in the digital age.

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