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GenHire: An AI-Based Resume Screening and Job Matching SystemUsing Model Context Protocol (MCP)

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Abstract

The development of online job sites has widened the scope of employment opportunities but has complicated the process of getting the right jobs to do. Old methods of job recommendation are based on the notion of key word matching, and thus are not in a position to detect contextual relationships between resumes and job descriptions. In this paper, the author introduces GenHire, an AI-powered resume screening and job matching algorithm that uses Generative AI and the Model Context Protocol (MCP) to enhance the accuracy of the recommendation. It pulls in skills via Natural Language Processing and matches them with job opportunities on sites such as LinkedIn and Naukri. The system offers scalable, precise and efficient recruitment solutions by integrating key word extraction, semantic interpretation and structured processing.

Introduction

The swift digitization of the recruitment process has greatly transformed the way people seek jobs. Industries that offer access to a high number of job posting and career opportunities now rely on LinkedIn and Naukri as the primary discoveries of jobs [1]. The increasing volume of information offered is, however, accompanied by new challenges as users will struggle to identify jobs that suit their skills, qualification and their future long term career goals [2]. Such information overload impedes productivity and complicates and increases the costs of the job search process.

The most popular job recommendation methods are founded on the classical approach of performing matching and information retrieval with keywords such as BM25 where the relevance is determined by the frequency of keywords and ranking of the documents [3]. Though these systems offer a simple filtering option, they do not have features of capturing contextual and semantic associations between resumes and job descriptions. This subsequently results in misinterpretation of similar skills in different terms and therefore no recognition hence irrelevant recommendations and failure to offer opportunities to applicants [4].To overcome these shortcomings, machine learning-based techniques have been proposed to enhance job recommendation systems. Such techniques are content based filtering and semantic similarity techniques to align more closely candidate profiles to job requirements [5]. Also, Natural Language Processing (NLP) has been extremely instrumental in deriving meaningful signals out of unstructured resume data, which allows a better comparison of the skills and talents of the candidate and the job description [6]. Despite these advancements, many of the existing systems still struggle with handling complicated format resume, multi lingual data and dynamic job specifications.The more recent developments with Large Language Models (LLM) have enabled systems to process and understand the information in text at a more complex level. The more detailed semantic analysis that can be afforded by the use of LLM-based solutions can enable systems to identify relationships between skills, experiences and job requirements not connected with mere key-word matching [7]. These models enhance the precision of job recommendations through capturing contextual meaning and contribute towards more intelligent ranking mechanisms.Also, the resume-job matching study has examined a variety of ranking and similarity-based techniques to enhance the performance of the suggestions. The methods to compare textual data such as TF-IDF and the cosine similarity have been widely employed to provide a foundation in semantic matching of recruitment systems [8]. More advanced systems come with hybrid methods that combine statistical methods with AI-based models to improve resilience and flexibility [9].Nevertheless, even after the advances in AI-based recruitment systems, there are still a number of challenges. Problems like data inconsistency, absence of structured context processing, and possible bias in automated decision-making still persist in influencing reliability and fairness of the system [10]. These concerns are a conversation on the need to have better structured, open, and scaled solutions that can effectively process the contextual information without affecting uniformity in outputs.In a bid to deal with them this paper proposes GenHire, a resume screening and job matching system that is an artificial intelligence and is intended to improve the relevancy and efficiency of job recommendations. It uses Natural Language Processing to search informative features on resumes and integrates Generative AI to provide the possibility of matching job descriptions with the context. GenHire unlike the traditional systems is based on the understanding of semantic relationships and does not just use the similarity of the keywords, thereby enhancing the accuracy of the recommendations.The system has also introduced the Model Context Protocol (MCP) to manage resume information, job information and processing logic in systematic and organized manner. MCP is a standardized context data management, which facilitates the reliability, scalability and consistency of systems in real world systems [11]. The system also has links to applications that enable users to easily transition between job discovery and application and this enhances their user experience.

The overall objective of the work is to create an intelligent, scalable and user friendly job recommendation system where the primary aim is to reduce manual effort in it, in addition to increasing accuracy and relevance. GenHire will fill this disconnect between advanced technologies of recruiting and what the practical user requires by combining Generative AI with the capabilities of managing context, which will provide a more effective and personalized job searching experience.

Literature Review

Recent improvements in machine learning, natural language processing, and artificial intelligence methods have seen the development of job recommendation and resume screening systems. Initial studies in this field were mainly centered on the traditional machine learning-based methods of job recommendation. Research like [1] examined content and collaborative filtering techniques to pair up candidate profiles to job requirements. The systems focused on enhancing the accuracy of the recommendations but were still constrained by the need to rely on structured data and predefined features.With the proliferation of recruitment platforms, there was an increasing demand to work with large and complicated textual data. In [2], it was proposed that transformer-based methods and semantic similarity models could be used to improve job recommendations. These methods allowed understanding the textual material more effectively as they used deep learning structures that do not rely solely on the matching of the keywords.Nevertheless, most systems still used information retrieval methods like BM25 to rank job applicants and resumes. The experiment described in [3] proved the usefulness of BM25-based the methodologies of shortlisting the applicants according to their relevance to the key words. These methods, however, were not very effective in capturing semantic meaning and contextual relations between resumes and job descriptions, resulting in lower accuracy in real world application.In order to overcome these shortcomings, the focus of research began to turn to Natural Language Processing (NLP)-based resume analysis. The methods suggested in [4] used the similarity measures and NLP to obtain the important features of resumes and compare them with job descriptions. Likewise, research like [5] underlined the significance of long-context modeling and semantic ranking to enhance person-job fit, as well as the significance of deep contextual insight in contemporary recommendation systems.Additional innovations featured AI-based systems that can produce personalized recommendations and enhance resume analysis. The literature in [6] was aimed at elucidating AI methodologies in order to provide transparency and equity in job recommendation schemes to counter the issues of prejudice in automated decision-making. Also, the paper [7] examined the techniques of expertise ranking and profiling in order to improve the process of candidate skill evaluation in large-scale systems.The combination of NLP and machine learning methods to resume-job matching has been widely researched in articles like [8] and [9], which suggested personalized matching systems and bibliometric reviews of AI-based research on recruitment. These papers showed how the use of intelligent models coupled with the use of statistical approaches is increasingly becoming significant in enhancing the effectiveness of the recommendation process.TF-IDF and cosine similarity are semantic similarity methods that have been extensively used to screen resumes and match jobs. The analysis in [10] underscored the usefulness of similarity-based methods in narrowing down on relevant candidates but the methods did not have profound contextual insight. In more recent studies, like [11], AI-based resume parsing and job matching systems have been proposed, which can make use of advanced NLP methods to enhance accuracy and scalability.As large language models have become popular, studies on explainable and context-aware AI systems have become a source of interest. The article in [12] introduced a multi-agent system based on LLM and Retrieval-Augmented Generation (RAG) to screen resumes, and it showed better transparency and flexibility in recruitment processes. Also, [13] discussed the proactive recommendation systems that help users in the process of writing, where timely and context-sensitive information retrieval is significant.The latest developments in agent-based architectures have further enhanced the integration of the AI systems in the real world applications. The research in [14] proposed the Model Context Protocol (MCP) that offers a formalized model of managing contextual information and incorporating various elements in AI-based systems. MCP facilitates coordination of the various modules involved, enhancing reliability and scalability of the system.Lastly, [15] suggested a holistic AI-based decision-making system in the hiring process which incorporates various sources of data, such as resume, interviews and public profiles. This framework illustrated that multimodal analysis coupled with structured evaluation and human-in-the-loop validation can be efficiently used to improve the efficiency of recruitment and the quality of decisions.

In general, the literature suggests that there is a clear evolution of the conventional keyword-based systems to the new AI-based, context-sensitive, and multi-agent systems. Although major gains have been realized in semantic understanding, scaling and automation, there still exists issues of bias, data inconsistency and absence of structured context management. The GenHire system proposed is based on these developments by incorporating Generative AI with a structured context processing via MCP and seeks to offer a more precise, scalable, and user-friendly job recommendation system.

Methodology

1. System Architecture

The suggested Gen-AI driven job recommender system is developed as a modular system, which incorporates resume processing, job data processing, contextual processing, and recommendation generation. Hiring systems based on AI combine resume analysis and skill matching with candidate ranking in a single pipeline [15]. The system has a structured workflow in which user input is handled and compared to job postings to come up with the relevant recommendations. The agent based architectures enhance modularity, scalability as well as reliability within AI systems [14]. The system architecture has been shown in figure.1

Resume Processing Module

It is initiated by the resume processing module, whereby users post their resumes on the system in PDF format. The uploaded document is transformed to text with the help of proper parsing methods. After extracting the text, it is processed using Natural Language Processing (NLP) and relevant keywords, skills, and other valuable information are identified, including experience and technical competencies. This will convert the unorganized resume information into an organized format which can be further analyzed. Systems that are based on NLP are able to derive pertinent skills and contextual data in resumes to enhance the quality of job matching and recommendation processes [3].

Job Dataset Module

The module of the job dataset will be composed of job ads found in websites like LinkedIn and Naukri. These vacancies are grouped into a structured data set with variables like job title, job description, skills required and links to apply to the job.The data are preprocessed to maintain uniformity in formatting and to eliminate redundant or unnecessary data. This is a structured data set, which is used to match user profiles with job opportunities..

Keyword and Contextual Matching Module
The system in this module matches the resume keywords extracted with job descriptions in the dataset. In contrast to the traditional systems where the matching process is based on direct key search only, the proposed system is based on the use of Generative AI to promote a better understanding of the context. Job-resume matching research has been advanced and changed greatly due to the emergence of NLP and machine learning approaches [9].The AI model examines the connections between the terms in resumes and job ads, which allows the system to draw the appropriate matches when the terminology is dissimilar. This enhances the precision of the recommendation process and minimizes the drawbacks of the key-word based methods. Transformer-based models are used to improve the contextual matching of resumes and job descriptions in advanced systems to make the recommendation more relevant [2].

MCP-Based Context Handling
The flow of information in the system is organized with the help of Model Context Protocol (MCP). It provides a controlled and structured way of dealing with various forms of data. The system separates:

- Context of resume (user data)
- Job context (job descriptions and requirements)
- Matching and analysis (processing logic)

This methodological system increases predictability and reliability in the output of the system and improves performance of the Generative AI model. More recent developments make use of multi-agent architectures based on LLM to conduct resume screening and evaluation [12].

Recommendation Module
The system produces a list of suggested job postings based on the outcome of a keyword and contextual matching. These tips are prioritized based on how it relates to the resume of the user. The model comparison graph showing ML vs GenAI job recommendation has been shown in Figure 1. The ranking is also affected by the level of similarity between job descriptions and resume content with the result that the best job opportunities are offered to the user.

Application Link Integration
All suggested jobs have a direct application link which is obtained in the dataset. This allows users access the job postings directly and apply without having to search them manually on third-party sites. The overall efficiency of the job search process is improved with the help of this integration, and the user experience is also improved.

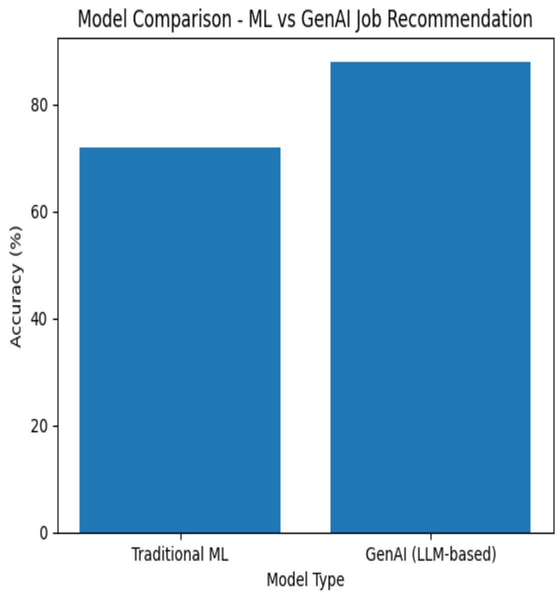

Figure 1: Model Comparsion- ML vs GenAI Job Recommendation.

System Workflow Overview
The overall workflow of the system can be summarized as follows:

1. User uploads resume
2. Text in resumes is extracted.
3. Keywords and skills are distinguished.
4. Process of Job dataset.
5. Generative AI is used to do contextual matching.
6. Relevant jobs are prioritized.
7. Recommendations that have application links.

The GenAI Job Recommender System Architecture has been shown in Figure 2.

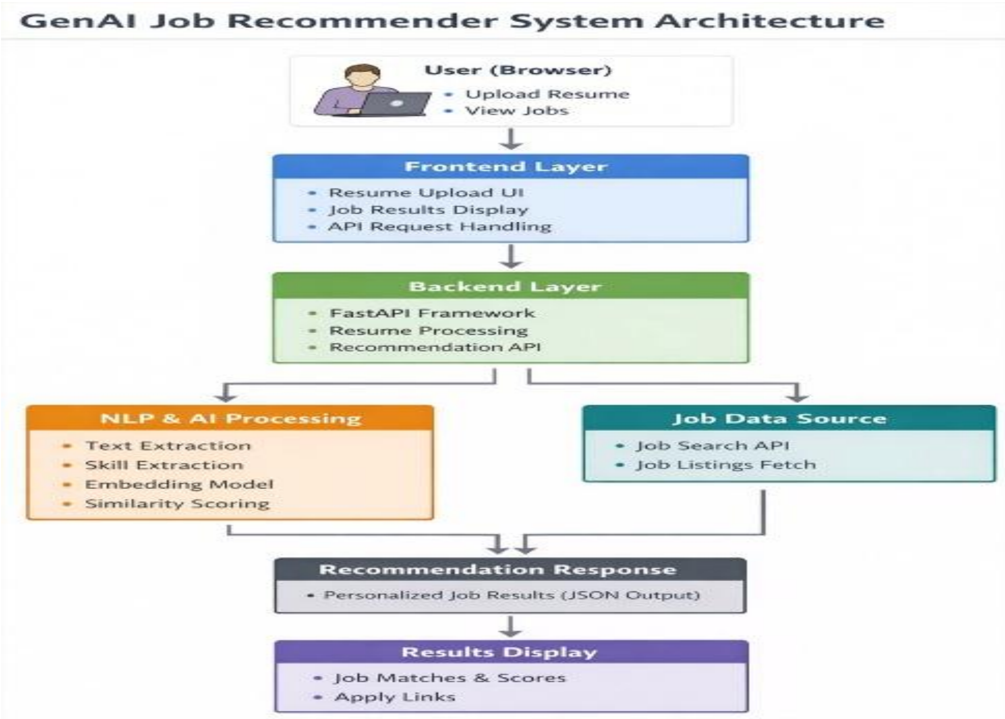

Figure 2: GenAI Job Recommender System Architecture.

Table 1: Summary report of the specifications derived from the requirements.

Module	Function	Description
Resume Processing	Text Extraction	Extracts text from uploaded resume (PDF)
NLP Analysis	Keyword Identification	Identifies skills and relevant terms from resume
Job Dataset	Data Storage	Stores job postings from LinkedIn and Naukri
Matching Module	Keyword & Context Matching	Matches resume content with job descriptions
Generative AI	Contextual Understanding	Enhances matching using contextual interpretation
MCP Framework	Context Management	Organizes resume data, job data, and processing logic
Recommendation Module	Job Ranking	Generates and ranks relevant job recommendations

2. System Implementation

The proposed Gen-AI powered job recommendation system implementation is aimed at the incorporation of the resume processing, keyword extraction, contextual analysis, and recommendation generation into one workflow. The system would be able to handle user input and produce a job recommendation in real time in an efficient way. Current AI systems employ organized pipelines that produce resume parsing, semantic analysis, and generative models to enhance job-related applications personalization [3]. Specifications derived from the requirements has been given in Table 1.

Detailed Workflow of the Proposed System

The proposed system workflow as has been described in this section. The system adheres to a series of well-organized steps to convert user input to valuable suggestions:

1. ResumeUpload:The application interface allows the user to upload his or her resume in the form of a PDF file.
2. 2.Text Extraction:The system will use parsing techniques to extract textual information on the uploaded resume.
3. Keyword Identification:Natural Language Processing (NLP) is used to extract the

relevant skills, technologies, and keywords in the resume.
4. Job Dataset Processing:The system receives the job postings within the dataset which contains job descriptions, skills required and application links.
5. Matching Process:The keywords of the resume extracted are matched with job descriptions. Generative AI helps to improve this step by allowing matching terms based on context.
6. Recommendation Generation:Using the results of the matching, the system creates a list of matching job recommendations ranked by similarity.
7. Application Link Display: Each of the suggested jobs has been directly linked in the system and users can apply effectively.

Key Functional Components
The system is implemented on the basis of integration of the following functional components:
- Resume Parser: Removes text of uploaded documents.
- NLP Module: Finds keywords and other features.
- Dataset Manager: Handles job postings and provides structured data.
- Matching Engine: Keyword and contextual comparison.
- Generative AI Module: Improves the understanding of resumes and job descriptions.
- MCP-Based Structure: Structures data processing and flow.
- User Interface: Presentation of results.

Generative AI Integration
Generative AI is also integrated to enhance the quality of job recommendations, which allows understanding the context. The AI model does not use the exact word matches as the way of identifying the results, but it examines the relations between various words used in resumes and job descriptions. Generative AI models are also able to dynamically personalize content depending on job descriptions and user profile, increasing personalization and relevance in recruitment systems [3].This enables the system to know the appropriate job opportunities even in cases where related skills are defined with dissimilar wording. Generative AI allows improvement of the accuracy of recommendations and offers more meaningful results.

MCP-Based Implementation
Model Context Protocol (MCP) is used to organize the data flow of the system. The implementation will ensure that:
- Data on the resumes is done individually.
- Handling of Job dataset is different.

This division enhances the predictability of the system and guarantees the uniformity of outputs of the Generative AI module.

System Output
The output of the system is:
- A list of suggested job advertisements.
- Ranking based on relevance
- Direct application links

This output format enhances usability and less effort is needed in search and application of jobs.Recommender systems strive to give proactive information, which enhances efficiency [13].

Implementation Advantages
The system implementation offers a number of benefits:
- Effective resume information processing.
- Better matching with contextual knowledge.
- Organized data processing by MCP.
- Simplified job application process.
- Scalable system design for future enhancements.

Results and Discussion
Gen-AI powered job recommender system proposed was tested in terms of its capability to provide relevant job recommendations given uploaded resumes. Although BM25-based systems offer effective ranking, they are not ideal at dealing with semantic similarity and contextual interpretation, which can be solved with generative AI-based solutions [4]. The system was evaluated on several sample resumes and a systematic set of vacancies gathered on websites, like LinkedIn and Naukri. Other studies also note that explainable AI is essential in recommendation systems so as to enhance transparency and user trust [2].

1. Recommendation Accuracy
The system proved to be more relevant in job recommendations than the conventional ones based on keywords. The system could find connections between resume text and job descriptions despite the use of different words as it included Generative AI to understand the context of the resume and the description of the job. Machine-learning-based systems have demonstrated better results when compared to the traditional systems that use keywords to give

relevant job suggestions [1]. As an illustration, the resumes with skills listed in different forms were effectively matched with relevant job advertisements, which was an indicator of the efficiency of contextual analysis. The model accuracy improvement has shown in Figure 3.

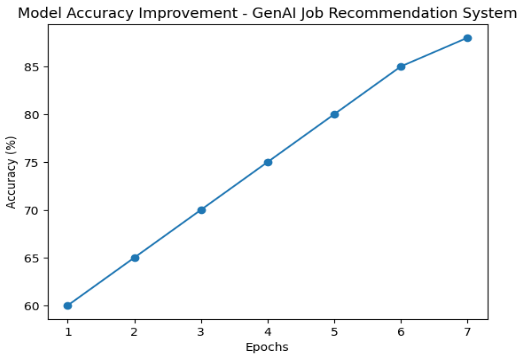

Figure 3: Model Accuracy Improvement.

2. Efficiency of the System

The system is effective in processing user input and generating recommendations in a limited amount of time. A combination of resume parsing, key word extraction and matching systems also provides a seamless flow between input and output. These systems should provide more precise, interpretable, and scalable job recommendations based on semantic understanding with the help of the LLM [5].The presence of direct application links also helps in minimizing the time that the users would have to use to apply to jobs thus enhancing system efficiency

3. User Experience

The system improves the experience of the users, who are made to search jobs easily. Users do not have to search through multiple job postings manually; they get filtered and ranked job suggestions based on their resume.

It is a well-structured output with direct links to applications, which offers a smooth flow of job discovery to application.

4. Analysis of System Performance

System performance has been analysed on the following factors:

- Relevance: Enhanced with the help of Generative AI contextual matching.
- Consistency: Maintained by using structured data processing with MCP.
- Scalability: The system can be scaled and expanded to bigger datasets and features.
- Usability: Streamlined interface and direct use links add to usability.

5. Limitations and Future Scope

In spite of the benefits, the system has its limitations:

- Reliance on resume content.
- Variations in job descriptions might have an influence on matching accuracy.
- Small dataset can be a constraint to the diversity of recommendations.
- These shortcomings can be dealt with in subsequent upgrades of the system.

The proposed Gen-AI-based job recommendation system is a solid base to further improvements and practical implementation. There are a number of enhancements that can be made to enhance the capabilities of the system and make it more effective. Among the key future development opportunities is the introduction of real-time job information on platforms like LinkedIn and Naukri via API or automated data pipelines. This would enable the system to provide up-to-date job recommendations and improve the diversity of available opportunities. Such advanced models as Sentence Transformers make it possible to provide semantic matching candidates and job descriptions [11]. Another important enhancement is the implementation of advanced ranking mechanisms. The suggestions are currently made on the basis of keyword and contextual matching but the next generation of the system can be personalized and improved using other factors like user likes, level of experience and location. It can also be expanded to incorporate skill gap analysis whereby the user can be informed of the missing skills needed to perform certain job functions. This would assist the users know how to enhance their profiles and how they can enhance their chances of being selected. Additional feature enhancements can be the addition of conversational interfaces, where the user can engage more actively with the system. This will improve usability and offer a more interactive experience. Also, the system can be improved to cater to various areas of domains and industries which means that it is flexible to a broader spectrum of job categories. When it comes to larger datasets, optimization techniques may be used to enhance the performance and scalability of the system. Enhancements in job applications AI-based resume boosting and automated content creation can also be further incorporated in future systems to enhance job application efficiency [3]. On the whole, the project has the potential future to become more personalized, bring a more comprehensive data integration, and become more intelligent using more sophisticated AI methods. Such enhancements will be able to make the system more detailed and scalable in terms of job recommendation.

Conclusion

GenHire offers a fast and effective solution to the current recruitment issues by combining the analysis of the resumes, finding of keywords, and the interpretation of the context. The system enhances job recommendations accuracy and relevance through the use of Generative AI to go beyond the traditional matching approach based on keywords. Model Context Protocol (MCP) has been included to provide systematic context data processing to provide consistency and reliability in the recommendation process. Moreover, it includes direct application links, which streamline the job application process, enhancing user experience. All in all, this paper shows the feasibility of the integration of Generative AI with ordered context control to develop smart, efficient and user-friendly job recommendation systems.

References

M. T. Islam and A. Rahman, "Machine Learning-Based Job Recommendation Systems, Techniques and Approaches Based on Bangladesh,"
2026 International Conference on Advanced Communications Technology (ICACT), 2026.

R. H. El-Deeb, W. Abdelmoez, and N. El-Bendary,"Explainable and Scalable Job Recommendation System using Transformer-based Text Summarization, Cross-Encoder Semantic Similarity, and Ensemble Learning," Procedia Computer Science, 2026.

R. Chaudhari, A. Jadhav, R. Lalge, Y. Jichkar, and B. G. Galande, "AI-Powered Personalised Resume And Email Generator Using LangChain," International Journal of Engineering Development and Research (IJEDR), 2026.

S. G. Lilhare, V. Borate, and Y. Mali, "An AI & ML based BM25-Driven Methodology for Shortlisting Job Applicant Resumes," International Journal of Advanced Research in Science, Communication and Technology, 2026.

W. Jouanneau, E. Jouffroy, and M. Palyart, "An Efficient Long-Context Ranking Architecture With Calibrated LLM Distillation: Application to Person–Job Fit," 2025.

J. Gelling, A. Urman, and A. Hannak, "Auditing the bias of conversational AI systems in occupational recommendations: A novel approach to bias quantification via Holland's theory," Journal of Computational Social Science, vol. 9, 2026. doi: 10.1007/s42001-025-00433-4.

W. Liu, Z. Yang, Y. Zhao, and X. Li, "RATE: Reviewer Profiling and Annotation-free Training for Expertise Ranking in Peer Review Systems," arXiv preprint arXiv:2601.19637, 2026.

S. Guo, "ResuMatcher: A Personalized Résumé-Job Matching System," Master's thesis, Texas A&M University, 2015.

S. Rojas-Galeano, J. Posada, and E. Ordoñez, "A Bibliometric Perspective on AI Research for Job-Resume Matching," The Scientific World Journal, vol. 2022, Article ID 8002363, 2022. doi: 10.1155/2022/8002363.

C. Daryani, G. S. Chhabra, H. Patel, I. K. Chhabra, and R. Patel, "An Automated Resume Screening System Using Natural Language Processing and Similarity," Topics in Intelligent Computing and Industry Design, vol. 2, no. 2, pp. 99–103, 2020.

P. K. Gudipati, "AI-Based Resume Parser and Job Matcher," Master's Project, California State University, Northridge, 2025.

F. P.-W. Lo, J. Qiu, Z. Wang, H. Yu, Y. Chen, G. Zhang, and B. Lo, "AI Hiring with LLMs: A Context-Aware and Explainable Multi-Agent Framework for Resume Screening," in Proc. CVPR Workshops, 2026.

M. C. Puerta Melguizo, L. Boves, A. Deshpande, and O. M. Ramos, "A Proactive Recommendation System for Writing: Helping without Disrupting," Proc. Academic Conference, 2006.

A. Gioè and V. Catalano, "Agent Engineering for the Enterprise: An MCP-Based Framework," Master's Thesis, Politecnico di Torino, 2025.

V. Filatova, A. Zelenchuk, and D. Filatov, "AI-Driven Decision-Making System for Hiring Process,"
arXiv preprint arXiv:2512.20652, 2025.