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AI-Driven resume insights: NLP for intelligent skills and experience extraction

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KEYWORDS

algorithmic bias, AI-driven hiring, CV screening, fairness, diversity, vector space correction, data augmentation, natural language processing.

ABSTRACT

This study explores effective methods to reduce algorithmic bias in AI-driven hiring, particularly in CV screening systems. As organizations increasingly adopt artificial intelligence to streamline recruitment, biases in data and algorithms threaten fairness and diversity in candidate selection. The research focuses on two key techniques—vector space correction and data augmentation—to mitigate these challenges. Vector space correction modifies word embeddings in natural language processing (NLP) models, ensuring equitable representation of demographic groups. Data augmentation improves dataset diversity by generating synthetic samples for underrepresented categories. Additionally, a hybrid approach combining these methods is assessed for enhanced outcomes. The findings demonstrate that both techniques significantly reduce bias, with the hybrid approach achieving the best balance between fairness and performance. This research provides practical guidance for developing ethical AI systems, helping organizations build fairer and more inclusive recruitment processes.

1. INTRODUCTION

1.1 BRIEF INFORMATION

AI-Driven Resume Insights is an intelligent system that uses Artificial Intelligence (AI) and Natural Language Processing (NLP) to automatically analyze resumes and extract important information such as skills, education, work experience, and qualifications.

The system processes unstructured resume documents (PDF/DOCX), converts them into structured data, and provides meaningful insights about candidates. This helps recruiters quickly understand candidate profiles and make better hiring decisions.

The project uses technologies such as React (frontend), FastAPI (backend), and NLP models to parse resumes and display extracted information in a user-friendly interface.This helps recruiters quickly understand candidate profiles and improves the efficiency of the hiring process.

1.2 PURPOSE

The main purpose of this project is to automate the resume screening process using AI and NLP techniques. It helps organizations quickly identify suitable candidates by analyzing their skills, qualifications, and experience automatically. This system reduces manual work and improves the overall efficiency of the recruitment process.

Objectives

- Extract important information from resumes automatically.
- Convert unstructured resume text into structured data.
- Help recruiters identify suitable candidates quickly.
- Reduce manual effort and improve recruitment efficiency.

1.3 MOTIVATION

In modern recruitment systems, companies receive hundreds or thousands of resumes for a single job position. Manually reading each resume is time-consuming and inefficient.

This motivated the development of an AI-based resume analysis system that can automatically understand resume content and highlight candidate skills and experience

The project aims to make the hiring process faster, smarter, and more efficient for recruiters.

♦ Reduce manual resume screening time.

♦ Improve accuracy in identifying relevant skills.

♦ Help HR teams make faster hiring decisions.

♦ Use modern AI technologies to solve real-world recruitment problems.

1.4 PROBLEM STATEMENT

Recruiters often face challenges when analyzing resumes because they come in different formats, writing styles, and structures. This makes manual screening slow and error-prone.

Manual resume screening requires significant time and may lead to missing qualified candidates.

Therefore, an intelligent system is required to automatically extract and analyze candidate information using Natural Language Processing techniques to support better hiring decisions.

Problem Statement:

The traditional resume screening process is manual, time-consuming, and inefficient, making it difficult for recruiters to quickly identify qualified candidates from a large number of applications. Therefore, an intelligent system is required to automatically analyze resumes and extract relevant information such as skills, experience, and education using Natural Language Processing techniques.

2. LITERATURE SURVEY

1. Resume Parsing using Natural Language Processing:

Resume parsing is an important application of Natural Language Processing (NLP) in recruitment systems. Traditional recruitment processes require recruiters to manually read and analyze resumes, which is time-consuming and inefficient. Researchers have proposed automated resume parsing systems that extract structured information such as skills, education, and work experience from unstructured resumes.

Many studies have used Named Entity Recognition (NER) techniques to identify important entities such as candidate names, skills, organizations, and job titles. NLP-based models can understand the structure of resumes and classify sections like education, experience, and projects.

Recent research also integrates deep learning models like BERT to improve the accuracy of resume information extraction. These models help systems understand contextual meaning and adapt to different resume formats. Such automated systems reduce manual workload and help recruiters analyze large numbers of resumes quickly.

Therefore, NLP-based resume parsing has become a key technology in modern recruitment platforms and intelligent hiring systems.

2. Machine Learning Techniques in Resume Analysis:

Machine learning techniques have significantly improved the performance of resume analysis systems. Earlier approaches relied on rule-based methods or keyword matching, which often failed to handle diverse resume formats. Modern systems use machine learning algorithms to automatically identify patterns and relationships within resume data.

Researchers have applied supervised learning techniques to train models on labeled datasets containing resumes and extracted information fields. These models can classify resume sections and identify candidate attributes such as skills, experience, certifications, and achievements.

Some studies have used algorithms like **Support Vector Machines, Decision Trees, and Neural Networks** to classify resume content. Deep learning models such as **Recurrent Neural Networks (RNN) and Transformers** are also used for sequence labeling and text understanding.

These methods improve the accuracy and scalability of resume screening systems, allowing organizations to process thousands of applications efficiently.

As a result, machine learning has become a fundamental component in intelligent resume analysis systems.

3. Named Entity Recognition for Skills and Experience Extraction:

Named Entity Recognition (NER) is one of the most widely used NLP techniques for extracting information from resumes. NER helps identify important entities such as skills, job titles, companies, educational institutions, and dates of employment.

In resume parsing systems, NER models analyze text and assign labels to relevant words or phrases. For example, programming languages, technical skills, or tools mentioned in a resume can be automatically recognized and categorized.

Researchers have used NLP frameworks like spaCy, NLTK, and Stanford NLP to implement NER-based extraction models. These tools enable systems to process resumes and convert unstructured information into structured datasets.

NER-based approaches are particularly useful in recruitment systems because they allow recruiters to quickly filter candidates based on specific skills or qualifications.

Studies have shown that NER-based resume parsers significantly improve the efficiency of candidate screening processes by automatically identifying relevant information from resumes.

Therefore, NER plays a crucial role in building intelligent resume analysis systems.

4. Resume Summarization and Candidate Profiling

Another important area of research in resume analysis is automatic resume summarization. Resume summarization aims to generate concise summaries of candidate profiles by extracting the most relevant information from resumes.

Researchers have developed NLP-based summarization techniques that highlight key skills, experience, and achievements of candidates. These systems help recruiters quickly understand candidate profiles without reading the entire resume.

Some modern systems use transformer-based models to generate summaries that capture both syntactic and semantic meaning of resume text. These models can analyze long documents and produce structured summaries of candidate qualifications.

Resume summarization also helps in candidate ranking systems where resumes are compared with job descriptions to determine the best match.

By providing clear and structured insights about candidate qualifications, resume summarization improves decision-making in recruitment processes.

Thus, automated resume summarization has become an important component in AI-based recruitment systems.

It leverages labelled datasets and historical transaction records to train classification models, enabling accurate detection of unusual behaviors. Natural language processing and process mining techniques further enhance the system by uncovering deceptive practices and irregularities in event logs.

5. AI-Based Resume Screening and ATS System:

Modern recruitment systems increasingly rely on Artificial Intelligence (AI) and Applicant Tracking Systems (ATS) to automate candidate screening. These systems use NLP algorithms to analyze resumes and compare them with job requirements.

AI-based resume screening systems can identify relevant skills, evaluate experience levels, and rank candidates based on their suitability for a job role. This reduces the need for manual resume screening and speeds up the hiring process.

Recent studies have shown that integrating NLP with ATS algorithms can improve recruitment efficiency by automatically extracting candidate information and matching it with job descriptions. These systems also help organizations avoid overlooking qualified candidates due to human error.

Furthermore, AI-based resume screening tools can analyze large datasets and provide insights about candidate profiles, skill trends, and hiring patterns.

With the rapid growth of AI technologies, intelligent resume analysis systems are expected to become an essential part of future recruitment platforms

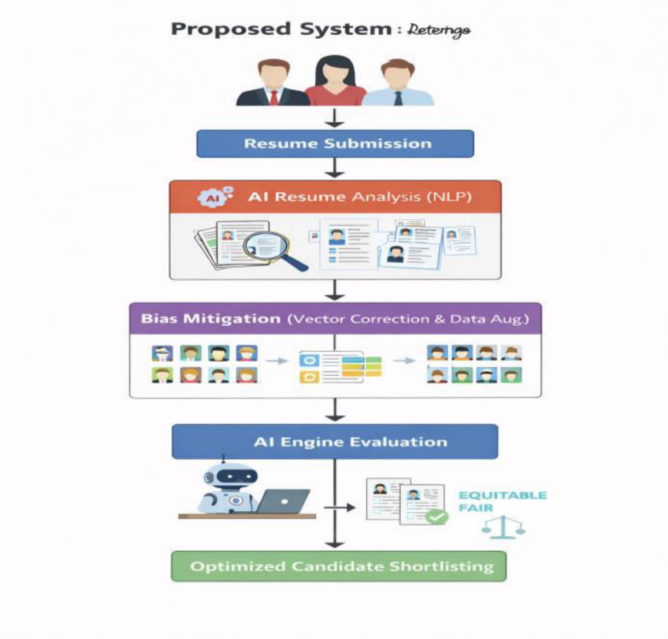
Various studies propose mobile applications, artificial intelligence, and IoT-based solutions to address challenges in plant care, plant identification, and agricultural management. These systems focus on improving plant health, reducing manual effort, and providing real-time assistance through smart technologies. Applications such as plant identification apps, AI-based disease detection systems, and reminder-based plant care systems highlight the importance of automation, accuracy, and user-friendly interfaces in modern plant management.

2.1 Existing system

The system automates resume analysis with NLP for contextual extraction (NER for skills/entities), bias mitigation (vector correction, data augmentation), and structured output (skills matching, summaries). It handles uploads, parsing, storage, and dashboards, reducing manual effort while promoting fairness across demographics via hybrid techniques.

Advantages include:

- Contextual understanding over keywords.
- Bias reduction for equitable hiring.
- Scalable processing of large resume volumes.
- Insights like skill-job matches and candidate rankings



3. PURPOSED SYSTEM

3.1 System Architecture

This layered design separates the system into clear components for efficiency and scalability. The User Layer (HR/candidates) interacts through a React-based Presentation Layer for uploads and dashboards. FastAPI manages API calls in the Processing Layer, where OCR, NLP parsing, skill extraction, and bias mitigation occur. The AI Model Layer performs NER and generates embeddings for matching and analysis. Finally, the Data Layer (MySQL/MongoDB) stores resumes and processed results. The flow is: upload → extract → mitigate bias → store/analyze → visualize.

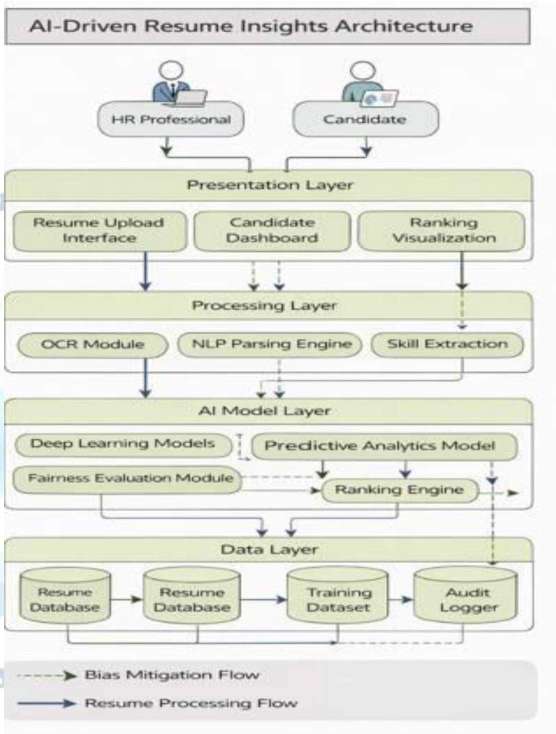


Fig 3.1: System Architecture

This diagram represents a layered resume screening architecture. HR users interact with the system through the React-based Presentation Layer, where they can upload resumes and view dashboards or rankings. The Processing Layer, managed by FastAPI, handles API requests and performs OCR, NLP parsing, skill extraction, and bias mitigation to ensure fair evaluation. The AI Model Layer (spaCy/BERT) applies Named Entity Recognition (NER) and semantic analysis to understand resume content and match it with job requirements using embeddings. The Data Layer (MySQL/MongoDB) stores resumes, extracted skills, and analysis results. Overall, the flow is: user upload → backend processing → AI analysis → data storage →

results visualization, ensuring modularity, fairness, and efficient candidate screening.

3.2 Use Case Diagram

This system has two main actors: the Recruiter and the Admin. The Recruiter can register/login, upload resumes, view insights, and rank candidates based on their skills and experience. When a resume is uploaded, the system may use OCR (if it's a scanned file) to extract text. It then parses the resume to identify important details like skills and work experience, applies bias mitigation to remove sensitive information, and generates insights. The system can also match candidates to specific job roles. The Admin manages users and system access. All data is stored securely, and the system can extend its functionality to generate reports for analysis and decision-making.

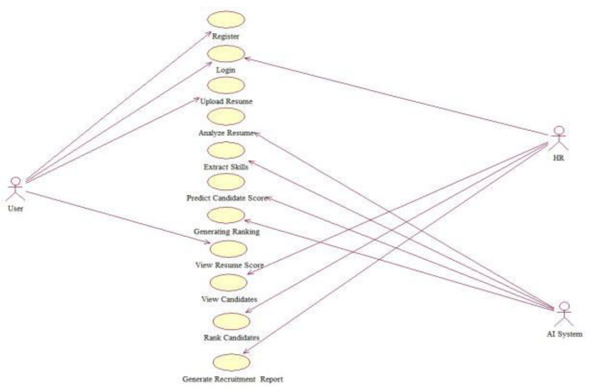


Fig 3.2: Use Case Diagram

This diagram shows how the system works step by step. The Recruiter can log in, upload resumes, view insights, and rank candidates. The Admin is responsible for managing users and controlling access.

When a recruiter uploads a resume, the system automatically includes the resume parsing process. It parses the resume, uses NLP to extract important details like skills and experience, and then applies bias mitigation to remove sensitive information. After processing, the system generates a clear summary of the candidate.

Additionally, the system can extend its functionality to perform job matching, where candidates are matched with suitable job roles, and recruiters can download a detailed report for further evaluation.

3.3 Class Diagram

This class design shows how different parts of the system are structured in code. The User class represents recruiters or admins and includes functions like login() and upload() to access the system and submit resumes. A User has a one-to-many relationship (1-*) with the ResumeParser, meaning one user can upload and process multiple resumes.

The ResumeParser class handles resume analysis with methods like extractSkills() and ner() to identify skills and named entities using NLP. After parsing, the data is passed to the BiasMitigator class, which reduces unfair influence using methods like vectorCorrect() and augmentData().

Finally, the InsightGenerator class processes the cleaned data to match candidates with jobs using matchJob() and rank them using rank(). Important attributes in the system include skills: List to store extracted skills and biasScore: float to measure potential bias in the resume data.

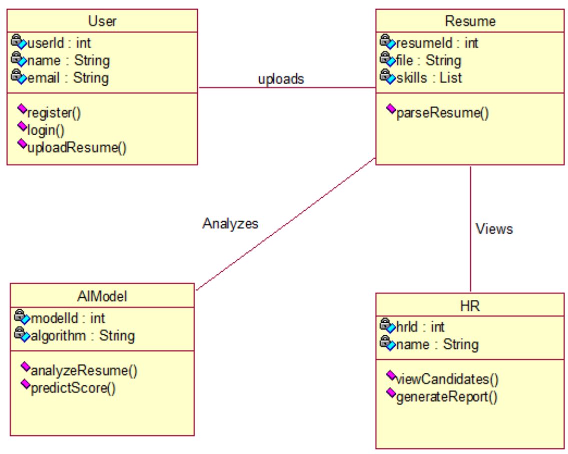


Fig 3.3: Class Diagram

This class diagram shows the structure and relationships between the main components of the system.

The User class represents system users (such as recruiters). It contains attributes like id:int and functions like login(). One User can be associated with multiple ResumeParser instances (1 to * relationship), meaning a single user can upload and process multiple resumes.

The ResumeParser class is responsible for analyzing resumes. It includes methods like extractText() to retrieve content from resumes and nerSkills() to identify skills using NLP techniques. Each ResumeParser is connected to one BiasMitigator (1 to 1 relationship), which ensures fairness in processing.

The BiasMitigator class contains methods such as correctVectors() to adjust embeddings and augmentData() to reduce bias in the dataset.

After bias mitigation, the processed data moves to the InsightGenerator class, which provides higher-level analysis through methods like matchJob() (to match candidates with job descriptions) and generateRank() (to rank candidates).

Finally, the Database class stores the extracted and processed data using storeExtracts(). It interacts with the InsightGenerator to save and retrieve results, ensuring persistent storage and data management.

4. RESULT

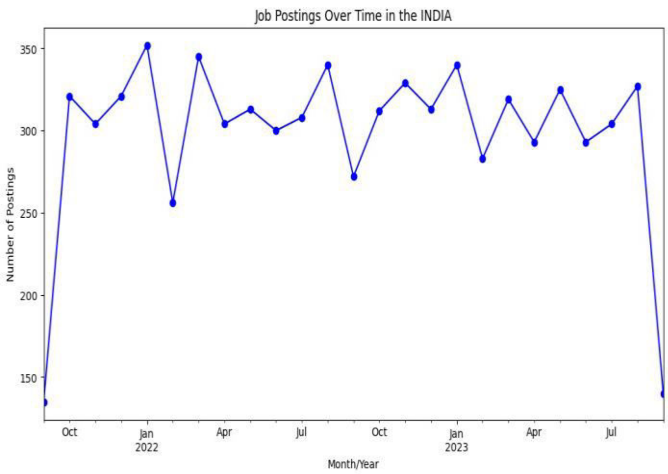


Fig 4. 1 Average Salary Range For Different Job Roles/Countries

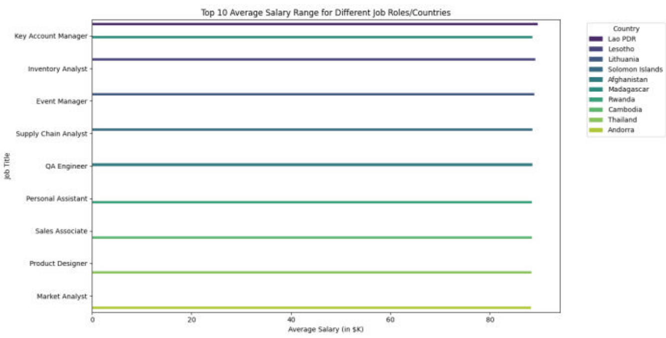


Fig 4.2 Job Postings Over Time In The India

Fig 4.3 Distribution of Work Types

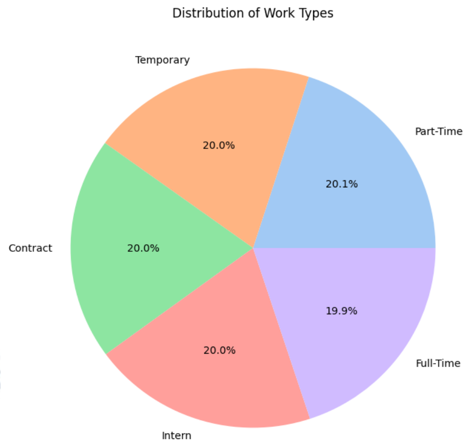


Fig 4.4 Top 10 Most In Demand Skills

Fig 4.5 Top Skills Required For Job

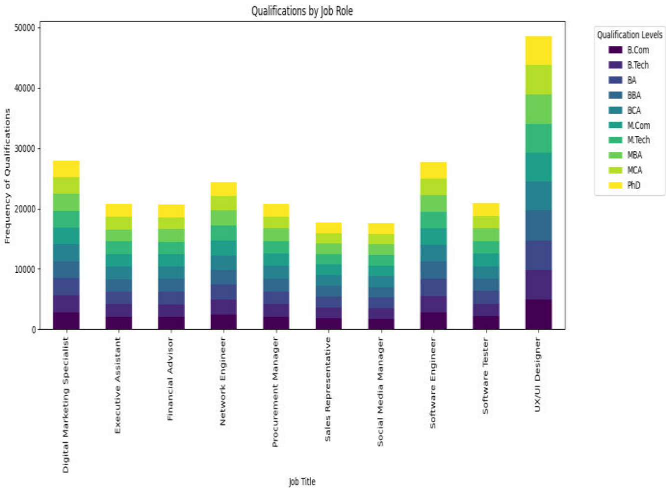


Fig 4.6 Qualification By Job Role

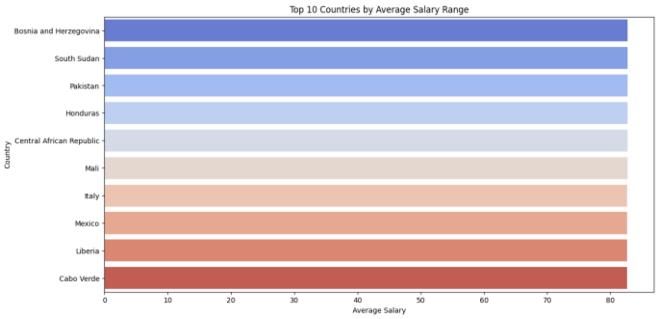


Fig 4.7 Countries by Average Salary Range

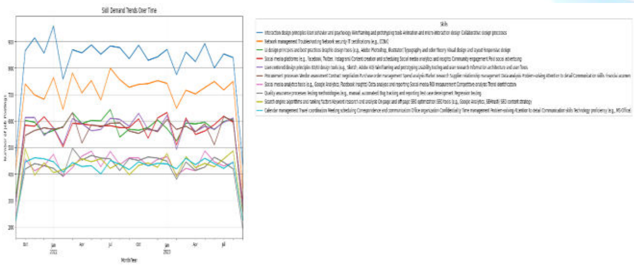


Fig 4.8 Skill Demand Trends Over Time

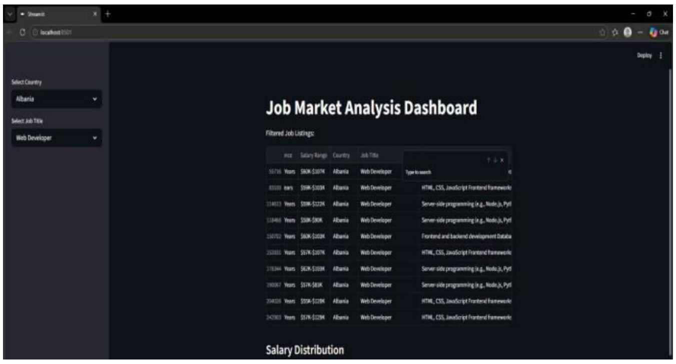


Fig 4.9 Job Marketing Analysis DashBoard

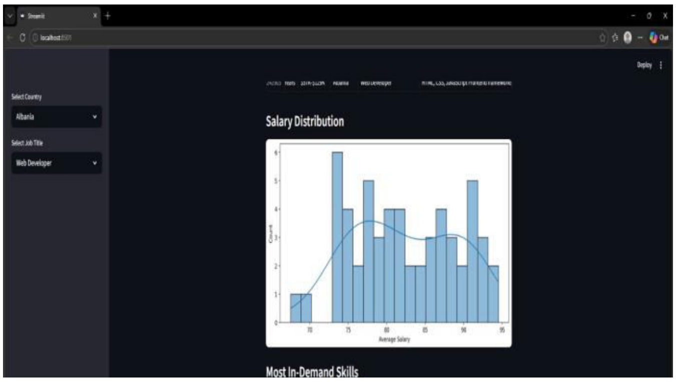


Fig 4.10 Salary Distribution

6. CONCLUSION

This study demonstrates that AI-driven hiring systems can be made fairer by leveraging vector space correction and data augmentation techniques. By modifying word embeddings, vector space correction ensures more equitable representation of different demographic groups, while data augmentation enhances dataset diversity, addressing biases in training data. The hybrid approach, which integrates both methods, achieves the most balanced results, significantly reducing bias while maintaining system performance. These findings provide valuable insights for organizations seeking to develop ethical AI-based recruitment processes. By implementing these techniques, companies can foster fairness, promote diversity, and build more inclusive hiring practices, ultimately leading to better workforce representation and decision-making in AI-driven talent acquisition.

FUTURE SCOPE

1. Refinement of Bias Mitigation Techniques Further advancements in vector space correction can enhance the accuracy of bias detection and mitigation in NLP models. Developing dynamic correction mechanisms that adapt to evolving linguistic and cultural trends will improve fairness in AI-driven hiring.

2. Integration with Explainable AI (XAI) Explainability in AI-driven resume screening remains a challenge. Future research can focus on integrating bias mitigation techniques with explainable AI frameworks, allowing recruiters to understand and validate model decisions.

3. Cross-Linguistic and Multicultural Applications Expanding bias mitigation techniques to support multilingual and culturally diverse hiring processes will be crucial. Research can explore how different languages and socio-cultural factors impact NLP-based recruitment tools.

4. Real-Time Bias Detection and Correction Implementing real-time monitoring systems that detect and correct bias dynamically during the hiring process will enhance fairness. Adaptive algorithms can continuously learn from new data and minimize emerging biases.

5. Ethical AI Frameworks for Recruitment Future studies can contribute to the development of standardized ethical guidelines and compliance frameworks for AI-driven hiring. Collaboration with policymakers and industry leaders can help establish regulatory measures.

6. Expansion to Other HR Functions Bias mitigation techniques can be extended beyond resume screening to other HR applications such as employee performance evaluation, promotion recommendations, and workforce planning, ensuring fairness across the entire employee lifecycle.

7. Hybrid Approaches with Deep Learning and Reinforcement Learning Combining vector space correction and data augmentation with advanced deep learning and reinforcement learning techniques can further improve the accuracy and fairness of AI-driven hiring systems.

8. Industry-Specific Customization Different industries require unique skill sets and evaluation criteria. Future research can explore industry-specific customization of AI models to ensure fair and effective hiring practices across various domains.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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