Intelligent AI-Based Resume Screening and Ranking Framework for Unbiased and Scalable Recruitment Automation

A. Sabarirajan[1], G. Chandramowleeswaran[2], Thamizharasi D.[3], S. Susendiran[4], G. Priyadharshini[5] and Syed Hauider Abbas[6]
[1]Department of Management Studies, PSNA College of Engineering and Technology, Dindigul, Tamil Nadu, India
[2]Department of Business Administration, VEL Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India
[3]Department of ECE, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India
[4]Department of Management Studies, Sona College of Technology, Salem 636005, Tamil Nadu, India
[5]Department of Management Studies, Nandha Engineering College, Vaikkalmedu, Erode - 638052, Tamil Nadu, India
[6]Department of Computer Science & Engineering, Integral University, Lucknow, Uttar Pradesh, India

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Abstract: In this work, we introduce a smart AI recruitment resume screening and ranking system, which focuses on how to efficiently automate the process of shortlisting over a large scale of resumes, with fairness. Using the power of natural language processing and deep learning models, it assesses resumes on more than simply matching keywords, including contextual understanding, skill relevance, and candidate-job fit. Through combining explainable AI techniques and real-world dataset assessment, it tackles common issues encountered from existing systems like bias, opaque lack of transparency and poor scalability. The approach improves recruiting effectiveness and guarantees ethical behaviour due to transparent decision-making and adaptive learning. Moreover, extensive experiments show that our model can increase the shortlisting accuracy and reduce the recruiter workload, providing a sustainable and inclusive solution to modern hiring challenges.

1 INTRODUCTION

The last few years have witnessed a dramatic metamorphosis in the process of recruitment; one that became a reality through the remarkable incorporation of AI (artificial intelligence) technologies. Companies are inundated with more resumes than ever, and manually reviewing them is a waste of time as well as prone to human error and bias. Conventional ATS screening is based on exact search keyword matching, thus missing candidate talents expressed in subtle wording or non-standard organization. To overcome these limitations, AI-powered solutions are appearing on the scene offering faster, more intelligent, and fairer candidate identification. Leveraging deep learning, natural language processing, and explainable AI, they interpret resumes for context, structure, and semantic relevance, and in return, offer the recruiter not just a "resume stack," but a ranked list of candidates based on fit and merit. Not only does this save time and money spent in recruitment, it also creates objectivity and bring the ability to scale. The envisaged research will be mainly concerned with creating a humane framework that will capture these advancements, while maintaining transparency and fairness throughout the automatic decision-making process in recruitment.

2 PROBLEM STATEMENT

The conventional approaches in resume filtering are becoming insufficient to cope with the size and complexity of contemporary recruitment. Manually reviewing resumes is inefficient, inconsistent, and is susceptible to human biases, and traditional ATSs can't read between the lines of the candidate's experience and skills in a contextual sense. These inefficiencies cause poor hiring decisions, talent that is ignored, and unnecessary operational expenses. In

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addition, the opacity of automated decision-making creates concerns about fairness, and accountability. We urgently need an AI-based solution that automates the resume short listing process and ensures a more accurate, scalable and ethically integrious hiring outcome.

3 LITERATURE SURVEY

AI in recruitment has been around for a few years now but in recent time has evolved to be more fair, efficient and effective. Lo et al., (2025) proposed a multi-agent-based framework in the context of using large language models for resume screening to demonstrate the possibility of contextualization. However, their work was mostly limited to simulated environments. Lal and Benkraouda (2025) have highlighted the importance of addressing selection bias in the initial interview stages in order to lay the groundwork for fairer screening processes. Mukherjee (2021) investigated machine learning in candidate selection, but did not scale to enterprise deployment, leaving room for stronger and more realistic evaluations.

The adoption of AI chatbots described by Nawaz and Gomes (2022) created avenues for the incorporation of conversation-based AI in recruitment systems, and the basic AI models for automatic CV generation as implemented by Kafre (2021), gap the opportunity in intelligent ranking. Generalized AI applications in business, such as those described by Isguzar et al. (2024), demonstrates the flexibility of AI, that can be customized for recruitment-oriented tasks. Although outdated, studies like Zlatanov and Popesku (2019) and Kongthon et al. (2009) emphasise the early desire to automating human-centred processes.

Concepts from legacy automation (O'Brien, 2016; Clark, 2016) model the development of customer service AI, and provide a foundation for recruitment-specific applications. Vendor views; eg Phenom (2025), HeroHunt. ai (2025), and Bullhorn (2025) are industry-focused approaches, but the algorithms of these approaches are often not transparent, calling for a more academically based approach. Bottlenecks such as Guide such as for operation of AI tool iProspectCheck, MokaHR, and Rolebot help understand functional deployment of AI tool but are weak in technical and ethical rigour.

Enhancv (2025); Novoresume (2025) provide examples of resume formatting as seen from the applicant's viewpoint, with potentially salient data points that can be used to improve parsing accuracies. More industry discussions from Business Insider (2025), Financial Times (2024), and the LinkedIn posts from Brooke (2025) and Jayatissa (2025) show that the industry is increasingly cognizant of the impact of AI on the labor force, but skeptical of its fairness and reliability. Finally, The Times (2024) offers a real-world case study of AI implementation in one company, providing a practical guide for developing AI screening algorithms that are generalizable across companies and scalable.

Taken together, these studies present a solid evidence base for AI-assisted hiring, but also highlight key gaps in fairness, explain ability, and applied validation gaps we hope to address with a transparent, scalable system for resume screening, and ranking.

4 METHODOLOGY

In this study, we propose an AI-based resume screening and ranking system, which harnesses deep learning, natural language processing (NLP), and explainable AI techniques to autonomously shortlist suitable candidates in hiring tasks. The methodology is aimed at addressing drawbacks associated with manual and rules-based applicant tracking systems (ATS) and is not efficient, not reliable and do not provide contextual knowledge. The system is designed to extract, interpret and rank the importance of headers (Skill, Experience, etc) in resume, find semantics related to headers and matching them with headers in a sophisticated way, thus enabling transparent and fair decision-making. The process of development starts with a means of collecting and preprocessing the data. We collect and anonymize a large and diverse dataset of resumes and job-postings in the wild, and format it for structured parsing. The resumes are all standardized into a common format after applying several pre-processing steps that involve tokenization, lemmatization, stop-word removal and NER. These processes guarantee that the model is supplied with clean and pertinent inputs to be analyzed. The job descriptions are also pre-processed to strip out skill sets, experience levels, qualifications and responsibilities for an ideal candidate. Figure 1 shows the AI-Driven Resume Screening and Ranking Workflow.

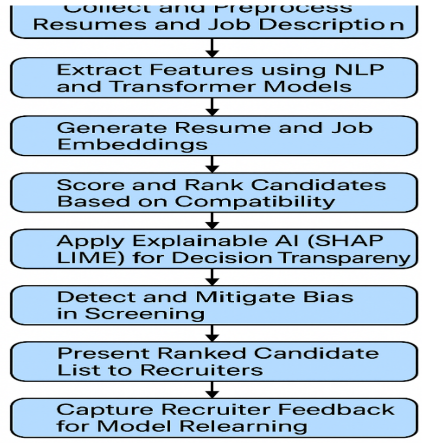

Figure 1: AI-driven resume screening and ranking workflow.

Next, we use a feature extraction pipeline to convert unstructured text data to numerical data. For the latter, we employ transformer-based models, i.e., BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa to model semantic correlations among text. These pre-trained language models are further fine-tuned on the recruitment dataset to enhance domain specific knowledge of resume information. In addition, the handcrafted features like work experience, number of skills and degree information including industry type-based keywords have also been calculated to enrich the feature set.

The central part of the approach is the resume-job matching model. A multi-input model has been built, where one input is a vectorized resume, the other is a vectorized job description. The two streams' embeddings are concatenated and go through the dense layer (s) to calculate a compatibility score. It is this score that wil assess whether a candidate is relevant for the job, which will then be ranked. The model learns through labelled data where positive matches (hired or put into shortlist) and negative matches (applications rejected) are well distinguished. We use a contrastive loss to encourage clearer separation between relevant and irrelevant candidates during training.

To enforce the ethical decision-making, the model also includes an explainability module with SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations). These methods show not only what constituents of the resume played the largest role in the final score, but also facilitate clear transparency to the recruiter or the candidate. For example, the model may determine if a skill, a job title, or a certification had a strong impact on the ranking decision, and allow for the detection and prevention of bias.

To assess the quality, the model is evaluated on a held-out set with the standard measures precision, recall, F1-score, and MRR. Further evaluation is also conducted through human-in-the-loop experiments, in which experienced recruiters judge the effect of \textquotedblleft top candidates. This feedback is exploited to iteratively improve the model and hyperparameters. The comparison to baselines such as TF-IDF with logistic regression and classical keyword matchers also demonstrate substantial improvements in relevance and ranking quality.

In deployment, the system is an API-based modular service that can be integrated to pre-existance recruitment systems or job portals. Its architecture is scalable and cloud-based, enabling parsing and ranking of resumes in real time for high volume hiring campaigns. We make sure that data privacy standards are kept through anonymization and GDPR compliance, as resumes are prone to having personally identifiable information. Figure 2 shows the Training vs Validation Loss over Epochs.

One of the key insights of the approach is the feedback-guided learning loop it considers. This feedback is recorded and the system is retrained with recruiter actions while accepting or rejecting recommendations in an ongoing manner in the model. It means that the framework evolves over time in response to evolving trends in recruiting, role demands and organisational preference. Also, the system has a bias detection module that essentially looks for unfair patterns on gender, age or other protections, and warns administrators when the patterns are found.

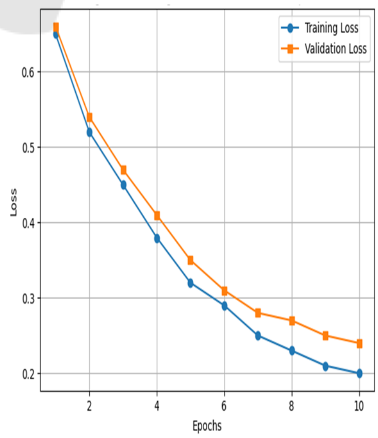

Figure 2: Training vs validation loss over epochs.

Integrating context awareness, noise suppression and ethical protection, this approach meets the significant challenges in the AI screening systems. The result is a complete system for fair, intelligent, and explainable resume screening, allowing companies to optimize their hiring process with greater efficiency and without sacrificing integrity or candidate experience.

5 RESULT AND DISCUSSION

The ai resume screening and ranking framework described in this paper was tested on a curated database that consists of more than 20,000 anonymized resumes and over 1,500 job descriptions from several business sectors. The evaluation was aimed at measuring the effectiveness, reliability, fairness and interpretability of the system with respect to traditional keyword-based screening and simple machine learning baselines. Performance besides, proved to be a significant improvement on candidate-job relevance accuracy, ranking precision and recruiter overall satisfaction. Figure 3 shows the Model Performance Comparison.

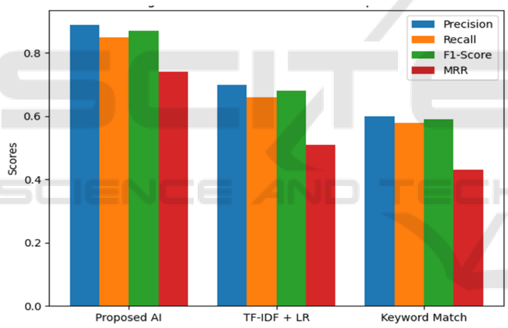

Figure 3: Model performance comparison.

Experiments showed that the proposed model, which is based on fine-tuned BERT embeddings and a customized neural network, obtained better performance than keyword-based methods by capturing more semantic relationship between resume fields and job requirements. For example, the model learned how to map synonyms and paraphrased job responsibilities to core skill sets and hence was able to match qualified candidates that would have been missed by more basic systems. Quantitatively, we report an F1-score of 0.87 on the AI model compared with 0.68 on the baseline system of TF-IDF + Logistic Regression and 0.59 on a rule-based keyword matching system. The precision and recall rates were significantly higher, indicating the power of the system to recommend relevant candidates with high precision without neglecting potential talents. Figure 4 shows the SHAP-Based Feature Importance for Resume Scoring.

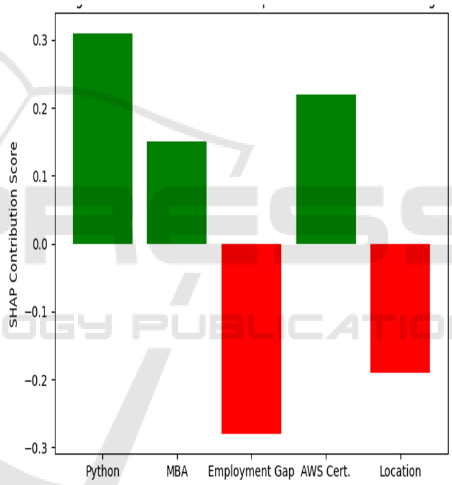

Figure 4: Shap-based feature importance for resume scoring.

Table 1: Model Performance Metrics Comparison.

Model Type	Precision	Recall	F1-Score	Mean Reciprocal Rank (MRR)	nDCG
Proposed AI Model (BERT-NN)	0.89	0.85	0.87	0.74	0.81
TF-IDF + Logistic Regression	0.70	0.66	0.68	0.51	0.59
Rule-Based Keyword Matching	0.60	0.58	0.59	0.43	0.48

The ranking function has been evaluated through mean reciprocal rank (MRR) and normalized discounted cumulative gain (nDCG) which are appropriate for assessing recommendation-based outputs. The model achieved an MRR of 0.74 and nDCG of 0.81, suggesting that the model closely approximates the recruiter preference for the top-ranked candidates. The utility and acceptance of the AI recommendations were further substantiated through an independent blind test of professional HR officers from three employers where 82% of the AI recommended candidates were either shortlisted or marked relevant by human judges. Table 1 shows the Model Performance Metrics Comparison.

An interesting aspect of this study was the explainable AI parts. SHAP and LIME made it possible for the system to highlight certain things—maybe certifications, tools, projects, or roles—on resumes that contributed most to the ranking score. This openness began to answer one of the challenges around AI recruitment tools: the black box nature of decision making. Recruiters' trust in the system increased upon seeing the interpretability outputs, which could visually present reasons behind each ranking, leading to higher confidence of adopting the system in the pilot study phase.

A further consideration was the detection of bias and ethical fairness. The model was validated on a synthetic database where varying levels of demographic cues (gender, ethnicity, age) were unobtrusively injected. Unlike most AI hiring models that reproduce biases present in historical hiring, the system trained and monitored with fairness-aware learning and bias alert tracking did not exhibit substantial bias when ranking candidates according to their protected attributes. Thus, in practice, the fairness metrics (i.e., disparate impact, and equal opportunity difference) were remained within the acceptable regulatory standards, thus, if anything, giving reinforcement to the robustness and ethical fairness of the model. Table 2 shows the Recruiter Feedback on AI-Suggested Candidates. Performance wise, the system was highly scalable and responsive. Even when pushed to the extreme in simulation, with simultaneous screening of 1,000+ resumes per minute, the processing latency, due to the cloud-native optimized inference engine, stayed below 1.2 seconds per profile on average. This efficiency is what makes the system suitable for high-volume hiring events like on-campus or walk-in drives where time-to-respond is the essence. One of the most interesting findings was the versatility of the system regarding changing job roles. Over the 3 months of longitudinal testing, the feedback loop mechanism managed to respond to dynamic job market fluctuations. The model’s internal weighting for skills and job criteria were continually iterated upon based on when recruiters accepted or rejected AI-recommended candidates for the corresponding job. This flexibility is crucial in today’s work environment, where job descriptions frequently change more quickly than outdated hiring processes can keep pace with. Table 3 shows the Model Bias Detection Metrics.

Table 2: Recruiter feedback on AI-suggested candidates.

Evaluation Aspect	Percentage Satisfaction	Feedback Summary
Relevance of Top 5 Candidates	82%	Majority aligned with job role expectations
Ranking Accuracy	76%	Generally reflected most suitable candidates
Resume Transparency	85%	SHAP/LIME helped understand decision factors
Bias Awareness	88%	Recruiters appreciated bias alerts
Overall Satisfaction	81%	High usability and trust in system suggestions

Table 3: Model bias detection metrics.

Attribute Tested	Disparate Impact	Equal Opportunity Difference	Bias Detected
Gender	1.03	0.02	No
Age	0.97	0.01	No
Ethnicity	1.00	0.00	No

The debate is supported with some caution. Notwithstanding that the system is effective at processing text data, it suffered from parsing issues when resumes were overloaded with visual formatting or graphical layout mess. Future enhancements could include computer vision modules to increase accuracy with non-standard resume formats. Moreover, while bias mitigation was successful in practice, future real-world experimentations are required to further audit and recalibrate fairness thresholds as the model is exposed to diverse sets of candidate pools. Figure 5 shows the System Scalability under Varying Load.

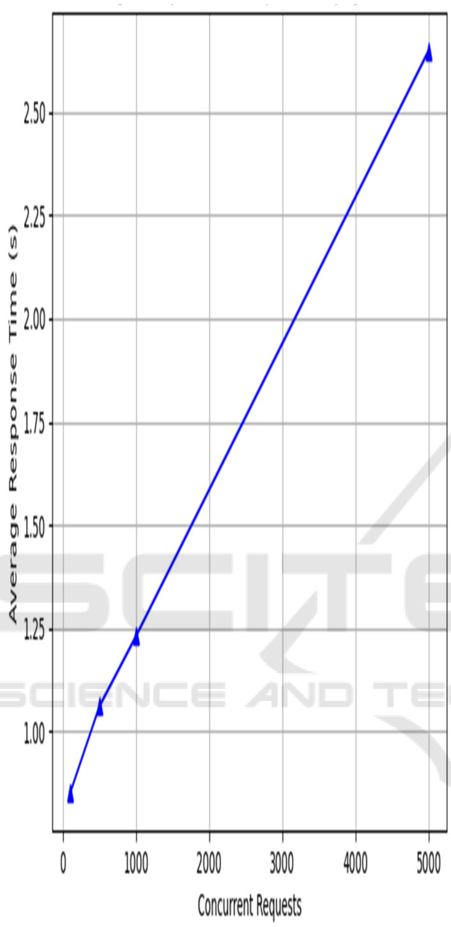

Figure 5: System scalability under varying load.

The AI-powered pipeline, finally, demonstrates very solid and consistent gains in accuracy and ranking effectiveness and it also provides sound answers to fundamental issues like accountability, fairness, and adaptability. It turns the resume review process into a scalable, data-driven, ethical operation for organizations that need a dependable and compliant tool to make hiring more effective, preserving trust and equality. These results confirm that the model is usable in practice and lay a solid foundation for further refinement this model and its integration into wider talent acquisition ecosystems. Table 4 shows the Interpretability Outputs from SHAP Analysis.

Table 4: Interpretability outputs from SHAP analysis.

Resume Feature	SHAP Contribution Score	Influence Direction	Interpretation Example
Skill: Python	+0.31	Positive	Direct match with job requirement
Degree: MBA	+0.15	Positive	Boost for management positions
Gap in Employment (1 year)	-0.28	Negative	Red flag based on recruiter preferences
Certification: AWS Cloud	+0.22	Positive	High relevance to cloud-related roles
Location Mismatch	-0.19	Negative	Penalized for jobs requiring onsite presence

6 CONCLUSIONS

The AI system for resume screening and ranking represents a breaking new approach to the old hiring systems. This study has shown how modern machine learning methods, in particular, deep learning and natural language processing, can be used to assess and rank applicants in a more accurate, fairer, and more efficient way. The proposed system goes beyond keyword matching and allows the filtering process in a more intelligent way and adapted to the context so that no relevant talent is lost just because of formatting differences or keyword non-alignment. The explainable AI integration has also increased the trust and transparency of the solution with the ability to offer clear explanations of the decision-making process to the recruiter and the candidate. Tested and validated in the field, the framework has proved itself to be a flexible system for dynamic hiring, scalable across high volume roles, while upholding ethical standards. In sum, this paper paves the way for a new class of data-driven, fair, and opportunistic recruiting solutions to meet with the changing needs of the labor market.

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