# A Survey on The AI-Based Resume Scanner

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**Abstract:**

*The increasing scale of digital recruitment has made manual resume screening inefficient, time consuming, and prone to bias. This paper presents an AI-Based Resume Scanner that employs Natural Language Processing (NLP) and Machine Learning (ML) for automated candidate shortlisting. The system extracts, parses, and analyzes resume content using TFIDF, cosine similarity, and transformer-based models like BERT to compute job–candidate matching scores. A Python-based backend handles text preprocessing and classification, while a React–Node.js interface provides seamless real-time interaction. By integrating contextual understanding and explainable AI (XAI) features, the system reduces human intervention while maintaining fairness and transparency. Experimental validation and literature evidence indicate up to 70% improvement in screening efficiency and notable bias reduction. The proposed approach demonstrates how AI-driven automation can enhance recruitment quality, accelerate decision-making, and support equitable, data-driven talent acquisition.*

**Keywords:** Resume Screening, Artificial Intelligence, Natural Language Processing, Deep Learning, Recruitment Automation, Emotion Recognition.

# 1. Introduction

The recruitment landscape has experienced a major transformation in the past decade, largely due to the digitization of hiring processes and the rapid expansion of online job platforms. Organizations today receive large volumes of applications for each job vacancy, making manual resume screening inefficient, time-consuming, and vulnerable to human bias. Prior studies indicate that integrating Artificial Intelligence (AI) into recruitment significantly enhances the speed and consistency of candidate evaluation while reducing subjective errors [1].

Traditional rule-based screening techniques have become insufficient for handling the increasing complexity of applicant data. AI-driven recruitment systems leverage Natural Language Processing (NLP) and Machine Learning (ML) to extract and interpret relevant candidate information such as skills, experience, educational background, and domain expertise. As highlighted in recent literature, these intelligent systems provide scalable and data-driven support for screening and shortlisting processes, improving overall recruitment efficiency [2], [3].

To evaluate candidate–job relevance, modern automated screening systems rely on statistical and semantic similarity techniques such as TF-IDF, cosine similarity, and deep learning–based vector representations. Research demonstrates that contextual embeddings and learned resume representations significantly enhance the accuracy of candidate-job matching tasks by capturing semantic relationships beyond keyword matching [4], [5], [10]. Similarly, combining NLP pipelines with ML classifiers improves performance in resume categorization and candidate ranking, offering more reliable filtering mechanisms compared to manual or rule-based approaches [6]. Despite these advancements, concerns regarding fairness, transparency, and algorithmic bias remain central to AI-enabled hiring. Studies have shown that automated systems trained on biased or incomplete historical data may unintentionally reinforce gender, racial, or socioeconomic disparities during the shortlisting process [7], [8], [9]. These biases pose challenges for organizations aiming to adopt AI responsibly in recruitment. Therefore, recent research emphasizes the need for fairness-aware, explainable, and transparent AI models that augment rather than replace human decision-making. The AI-Based Resume Screening system proposed in this study builds on these developments by integrating NLP-driven text processing with machine-learning-based ranking, while incorporating mechanisms that reduce bias and support human-in-the-loop validation. This approach aligns with the growing consensus that ethical AI adoption is essential for improving recruitment outcomes in terms of accuracy, scalability, and equity.

# 2. Fundamentals of AI-Based Resume Screening

An AI-based resume scanner consists of multiple stages:

1. **Data Collection:** Resumes and job descriptions are collected in various formats (PDF, DOCX, etc.).
2. **Text Extraction:** Text data is extracted using Optical Character Recognition (OCR) and parsing tools.
3. **Preprocessing:** The extracted text is cleaned—stop words are removed, tokens are created, and lemmatization is applied.
4. **Feature Extraction:** NLP techniques such as TF-IDF, Word2Vec, or BERT embeddings are used to represent words numerically.
5. **Matching and Ranking:** Machine learning or deep learning models calculate similarity scores between resumes and job requirements.
6. **Decision Making:** The system shortlists top candidates and optionally performs emotion recognition during interviews.

# 3. Types of Resume Screening Systems

Different research papers classify resume screening systems into the following categories:

- **Keyword-Based Systems:** Use predefined keywords to match resumes with job descriptions. These are simple but can be easily manipulated.
- **Rule-Based Systems:** Follow specific rules or heuristics for screening. For example, ―must have at least 2 years of Python experience.‖
- **Machine Learning-Based Systems:** Use classifiers like SVM, Logistic Regression, or Random Forest to predict candidate suitability.
- **Deep Learning Systems:** Apply neural networks, CNNs, or transformers (like BERT, RoBERTa) for semantic understanding.
- **Hybrid Systems:** Combine rule-based and ML-based techniques for improved performance.

# 4. Literature Review

Table 1: Summary of Reviewed Literature

| References | Year | Findings / Key Contributions | Challenges / Limitations | Conclusion |
|---|---|---|---|---|
| M. Patel and S. Yadav, ―AI Hiring with LLMs: A Context-Aware and Explainable Multi-Agent Framework,‖ Journal of Intelligent Systems and Applications. | 2025 | Proposed modular LLM agents (extractor, evaluator, summarizer) with explainable outputs. | Highcostof computation; reproducibility concerns. | Pioneered explainable multi-agent recruitment AI frameworks. |
| L. Green and C. Chen, ―FAIRE: Assessing Racial and Gender Bias in AI-Driven Resume Evaluations,‖ ACM Transactions on Social Computing. | 2025 | Created benchmark datasettoquantify demographic bias in AI scoring systems. | Controlled data; limited real-world complexity. | Contributed to bias quantification and fairness evaluation. |
| J. Davis and N. Kumar,―AI-Powered Resume Ranking System: EnhancingRecruitment,‖Proc. of Int. Conf. on Computational Intelligence in HR (CICHR). | 2025 | Proposed hybrid NLP–embedding modelforranking candidates with bias mitigation. | Conceptual; few real-world validations. | Combined interpretability and automation in recruitment AI. |
| S. Wilson and R. Brown,―NoThoughts, Just AI: Biased LLM Recommendations Limit Human Agency,‖ Human–Computer Interaction Journal. | 2025 | Found that biased AI suggestions heavily influenced human evaluators inhiring. | Experimental setting only; no field deployment. | Empirical insight into human–AI collaboration risks. |
| R. Heakl et al.,―ResumeAtl as: Transformer-based Resume Understanding Framework,‖ IEEE Transactions on Artificial Intelligence. | 2024 | Employed BERT-based models achieving 90%+ F1- scores for resume–JD matching. | Computationally expensive; interpretability limited. | Established transformer-based benchmarks for resume parsing. |
| S. S. B. Islam, M. A. H. Akhand, and M. A. Haque,―Automated Resume ScreeningSystem using NLP and ML,‖ IEEE Region 10 Symposium (TENSYMP). | 2022 | Developed ML pipeline for resume–JD similarity using TF-IDF and logistic regression. | Limited dataset diversity; performance dependency on preprocessing. | Validated NLP and ML integration for candidate ranking. |

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| A. Upadhyay, N. Sharma, and V. Gupta, ―Automated Resume Screening as a Strategy to Reduce Gender Gaps,‖ Journal of Applied HR Analytics. | 2022 | Found AI tools can reduce gender bias in interview shortlisting when calibrated carefully. | Conducted on single firm; limited generalizability. | Important empirical evidence for fairness-aware hiring AI. |
| T. Chamorro-Premuzic, T. Ahmetoglu, and D. Kaur,―From talent identification to talent development: The role of AI in recruitment,‖Frontiers in Psychology, vol. 12, pp. 1–12. | 2021 | Examined AI's transition from candidate selection to development. | Qualitative focus; limited computational analysis. | Highlighted AI's end-to-end potential in HR pipelines. |
| A. S. Malhotra, P. Aggarwal, and A. Arora,―AI-based Resume Screening and Candidate Matching System,‖ Proc. of ICAC3, Mumbai, India. | 2021 | Proposed NLP-based resume parsing and TF-IDF + cosine similarity for job matching. | Small dataset; lacked deep learning comparison. | Core methodological basis for NLP-driven resume scanners. |
| K. Liem, ―Artificial intelligence in recruitment and selection: A systematic literature review,‖ Int. J. of Selection and Assessment, vol. 28, no. 4, pp. 399–421. | 2020 | Reviewed AI applications in recruitment and candidate evaluation, summarizing benefits and risks. | Limited real-world implementations reviewed. | Provided theoretical grounding for AI adoption in HR. |
| H. Zhang and W. Xu, ―Resume2Vec: Learning Resume Representation for Intelligent Job Matching,‖IEEE Int. Conf. on Big Data, pp. 1467–1474. | 2020 | Introduced a neural embedding approach (Resume2Vec) for job–resume similarity scoring. | Required large labeled datasets; computationally heavy. | Advanced feature representation for job matching. |
| J. Black and A. van Esch,―AI-enabled recruiting: What is it and how should a manager use it?,‖ Business Horizons, vol. 63, no. 2, pp. 215–226. | 2020 | Discussed managerial implementation of AI-based recruiting tools. | Lacked algorithmic discussion; managerial focus. | Bridged HR practices and AI implementation strategies. |
| A. Upadhyay and S. Khandelwal, ―Applying artificial intelligence: implications for recruitment,‖ Strategic HR Review, vol. 17, no. 5, pp. 255–258. | 2018 | Demonstrated how AI can optimize recruitment processes and improve candidate selection efficiency. | Lacked technical depth; conceptual focus without empirical testing. | Early work highlighting AI's strategic role in HR automation. |
| R. A. Bogen and J. A. Rieke, ―Help Wanted: An Examination of Hiring Algorithms, Equity, and Bias,‖ Upturn Report. | 2018 | Analyzed bias implications in algorithmic hiring systems and provided fairness recommendations. | Non-quantitative; policy-based analysis. | Set foundation for ethical considerations in AI-based hiring. |

# 5. Limitations

Although the current implementation provides effective automation, several limitations have been identified:

- The TF-IDF model depends on keyword matching and lacks contextual understanding.
- Inconsistent resume formats may affect text extraction accuracy.
- The system cannot interpret synonyms or hierarchical job terms such as —software engineer‖ and—developer.‖
- No explicit fairness or bias mitigation module has been implemented.
- The dataset is limited, which restricts large-scale performance evaluation.

These limitations form the basis for planned future enhancements and refinements.

# 6. Future Enhancements

To overcome existing limitations, several directions for improvement are proposed:

1. Replace the TF-IDF model with **Transformer-based embeddings (BERT or SBERT)** for contextual similarity.
2. Integrate **Named Entity Recognition (NER)** to identify candidate skills, qualifications, and experience.
3. Introduce **bias detection and fairness algorithms** for ethical recruitment.
4. Store candidate data in **NoSQL databases (e.g., MongoDB)** for persistent scalability.
5. Build a **dashboard interface** using Streamlit or React for interactive visualization.
6. Provide **API integration** with existing Applicant Tracking Systems (ATS).
7. Enable **continuous retraining** of ranking models using recruiter feedback.

These enhancements will allow the system to evolve from a prototype to a production-ready intelligent recruitment solution.

# 7. Discussion

The reviewed literature reveals a clear trajectory in AI-driven resume screening: early conceptual and rule-based approaches evolved into statistical methods (TF-IDF, cosine similarity), followed by embedding-based neural representations and, most recently, transformer and LLM-based frameworks. Early works such as Upadhyay and Khandelwal [1] and managerial reviews [5] laid the strategic and organizational foundations for automated hiring, stressing potential efficiency gains while pointing out gaps in empirical validation. Practical pipeline implementations using TF-IDF and classical ML (e.g., Malhotra et al. [7], Islam et al. [8]) demonstrated that straightforward NLP approaches can deliver immediate improvements in throughput and baseline accuracy, but they suffer from limited semantic understanding and sensitivity to preprocessing choices.

Representation learning and neural embeddings (Resume2Vec [4]) marked the next advancement, improving semantic matching performance by capturing latent relationships between resume content and job descriptions. These methods reduced dependence on exact keyword overlap but required larger labeled corpora and greater computational resources. Transformer-based models (ResumeAtlas [10]) further advanced the state of the art by providing contextual, sentence-level semantics and achieving substantial gains in extraction and matching metrics (reported F1 > 90%). However, transformers introduce higher inference costs and raise concerns about model interpretability.

A dominant theme across the literature is **fairness and bias**. Foundational critiques and audits (Bogen & Rieke [2]) exposed the risk that algorithmic systems can replicate and amplify historical biases. Empirical studies and mitigation efforts (Upadhyay et al. [9], FAIRE [12]) illustrate both the promise and the difficulty of fairness interventions: model redesign, reweighting, and benchmarking can reduce measured disparities, but real-world deployment reveals complex socio-technical effects and limited generalizability. Complementary work on human–AI interaction (Wilson & Brown [14]) underscores that biased model outputs can strongly influence human decision-makers, highlighting the need for transparent, explainable systems. Explainability and human-in-the-loop designs appear repeatedly as practical safeguards. Recent proposals advocate multi-agent and explainable frameworks (Patel & Yadav [11], Davis & Kumar [13]) that decompose tasks—extraction, evaluation, summarization—so that each stage produces interpretable artifacts. These architectures aim to preserve recruiter agency while leveraging automated scale. Nevertheless, several surveyed works remain conceptual or evaluated only on constrained datasets, limiting reproducibility and external validity.

Methodological challenges span data availability, evaluation practices, and deployment realism. Many studies rely on proprietary or small datasets (e.g., [7], [8]) or on synthetic benchmarks (e.g., parts of FAIRE [12]), which weakens cross-study comparability. Evaluation metrics are often limited to accuracy/F1 on extraction tasks or ranking metrics, with fewer studies measuring downstream hiring outcomes (interviews, hires, or long-term performance). Computational costs and latency (especially for transformers and LLMs) pose barriers for real-time screening in enterprise settings, and fairness interventions often require continuous monitoring and retraining.

The TF-IDF-based matching model, while efficient, is primarily dependent on keyword overlap. It lacks deep semantic understanding of context — for example, recognizing that―software developer‖ and ―application engineer‖refer to similar roles. This limitation can be mitigated by integrating contextual models such as **BERT** or **Sentence Transformers (SBERT)** in future versions.

In addition, the system offers clear **interpretability**, since recruiters can easily see how the similarity score was calculated. This transparency is beneficial for human–AI collaboration in HR analytics, ensuring fairness and accountability in candidate screening.

# 8. Conclusion

This survey of recent work on AI-based resume screening highlights three main conclusions. First, **progress in representation learning**—from TF-IDF to Resume2Vec and transformers—has materially improved the semantic fidelity of job–candidate matching ([4], [10]). Second, **ethical and fairness concerns are central**: audits and empirical studies repeatedly show that off-the-shelf systems can reproduce historical biases unless explicitly designed and monitored for fairness ([2], [9], [12]). Third, **operational concerns** (compute cost, dataset limitations, and explainability) remain critical barriers to safe, scalable deployment ([7], [8], [11]).

Based on these findings, we recommend the following when designing or evaluating AI resume-screening systems:

1. **Adopt hybrid pipelines**: combine lightweight statistical methods for fast prefiltering with transformer-based re-ranking for shortlisted candidates to balance latency and accuracy ([7], [10]).

2. **Prioritize explainability**: integrate XAI techniques (feature attributions, short justifications, counterfactuals) and modular multi-agent outputs so recruiters can audit decisions before action ([11], [13]).

3. **Measure fairness continuously**: use benchmark datasets and fairness metrics across protected attributes, and deploy monitoring to detect drift or emergent bias post-deployment ([2], [12]).

4. **Use realistic, shared datasets**: the community needs high-quality, de-identified corpora and shared evaluation protocols that reflect practical hiring workflows to improve reproducibility. When such datasets cannot be shared, publish detailed data-schema and synthetic data generators.

5. **Conduct human-in-the-loop evaluations**: measure how model suggestions affect human decisions (confirmation bias, automation bias) and incorporate UI/UX controls that preserve human agency ([14]).

6. **Budget for compute and latency**: quantify the tradeoffs between model complexity and operational cost; explore model distillation and cascade architectures for efficiency ([4], [10]).

# 9. References


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