

# A Comprehensive Survey on Automated Resume Screening System Using NLP

BHASHKAR BISWAS<sup>1</sup>, DR. TARIQ SIDDIQUI<sup>2</sup>

<sup>1</sup>M.Tech. Scholar - CSE Department, Bhabha University, Bhopal, M.P., India

<sup>2</sup>Associate Professor, CSE Department, Bhabha University, Bhopal, M.P., India

*Abstract - Automated resume screening and job recommendation systems have emerged as important applications of Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) in modern recruitment processes. These systems aim to automate candidate evaluation by extracting relevant information from resumes and matching it with job requirements, thereby reducing manual effort, screening time, and recruitment costs [1], [2], [21]. Recent advancements in NLP techniques, including named entity recognition, semantic similarity computation, transformer-based language models, and Large Language Models (LLMs) have significantly improved the efficiency and accuracy of candidate-job matching [11], [23], [24], [29]. This survey reviews recent developments in automated resume screening and job recommendation systems published between 2018 and 2026. A detailed analysis of representative studies is presented, focusing on their objectives, methodologies, limitations, and research contributions. The survey identifies common challenges such as limited semantic understanding, lack of large-scale benchmark datasets, insufficient fairness evaluation, and dependence on keyword-based matching approaches [1], [4], [8], [10], [35]. Based on these findings, a conceptual research framework is proposed to integrate advanced NLP techniques with fairness-aware candidate ranking mechanisms. The survey provides valuable insights for researchers and practitioners interested in developing intelligent, explainable, and transparent recruitment systems [11], [12], [30].*

*General Terms: Artificial Intelligence, Natural Language Processing, Recruitment Automation, Resume Screening, Job Recommendation.*

*Keywords: Resume Screening, NLP, Job Recommendation, Candidate Ranking, Semantic Matching, Fairness, Recruitment Analytics.*

## I. INTRODUCTION

Recruitment is one of the most critical functions within human resource management, directly

influencing organizational productivity and long-term success. With the increasing number of online job applications, recruiters often face the challenge of processing hundreds or even thousands of resumes for a single position. Manual screening of such large volumes of applications is time-consuming, costly, and susceptible to human bias. Consequently, organizations are increasingly adopting AI-driven recruitment solutions to automate resume screening and candidate selection processes [1], [2], [4], [21].

Automated resume screening systems utilize Natural Language Processing techniques to analyze unstructured resume documents and transform them into structured information suitable for computational processing. Information such as technical skills, educational qualifications, certifications, work experience, and project details can be extracted automatically and compared with job requirements to identify suitable candidates [1], [8], [9], [22]. These systems not only accelerate the recruitment process but also help recruiters focus on the most relevant applicants.

Recent studies have demonstrated the effectiveness of NLP-based recruitment systems in improving candidate-job matching. Saatçı et al. [1] proposed a resume screening framework that combines NLP preprocessing techniques with Jaccard similarity measures to rank candidates according to job requirements. Similarly, Alsaif et al. [2] developed a bidirectional recommendation system capable of recommending jobs to candidates and suitable candidates to recruiters through named entity recognition and semantic similarity analysis. Other researchers have explored machine learning-based classification approaches, resume parsing frameworks, recommendation systems, and AI-driven

ranking models to improve recruitment efficiency and accuracy [3], [9], [13], [16], [26], [33].

Despite these advancements, several limitations continue to hinder the practical adoption of automated recruitment systems. Many existing approaches rely heavily on keyword matching or shallow similarity measures such as cosine similarity and Jaccard similarity, which often fail to capture semantic relationships between different terms and skill representations [1], [8], [15], [27]. Furthermore, the majority of studies are evaluated on relatively small datasets and lack standardized benchmarks, making direct comparison difficult [2], [9], [10], [25]. Issues related to algorithmic fairness, explainability, and bias mitigation also remain underexplored despite their growing importance in AI-driven decision-making [11], [12], [21], [35].

In addition, recent developments in transformer-based language models and Large Language Models (LLMs) have created new opportunities for enhancing resume screening and job recommendation systems. Advanced models such as BERT, Sentence-BERT, transformer-based classifiers, and LLM-powered recruitment agents can provide deeper semantic understanding of candidate profiles and job descriptions, potentially overcoming the limitations of traditional keyword-based methods [11], [23], [24], [28], [29], [30].

Recent studies have also explored multimodal recruitment systems, AI-powered resume analyzers, and recommendation frameworks that combine

semantic matching with intelligent ranking mechanisms. These approaches demonstrate promising improvements in recruitment accuracy and user experience, while also highlighting the need for scalable, explainable, and deployment-ready solutions for real-world hiring environments [31], [32], [34].

Therefore, this survey aims to provide a comprehensive review of recent research on automated resume screening and job recommendation systems using NLP. The study analyzes existing methodologies, compares their strengths and limitations, identifies key research gaps, and proposes a conceptual framework for future research. By synthesizing findings from recent literature, this survey seeks to contribute to the development of more accurate, fair, explainable, and intelligent recruitment systems [4], [6], [11], [20], [30], [35].



Figure 1. General Architecture

## II. LITERATURE REVIEW

Table 1. Summary of Key Literature Studies

Ref.	Study	Objective	Methodology	Limitation
[1]	Saatçı et al. (2024)	Automate resume screening and candidate ranking	NLP preprocessing, SpaCy NER, Jaccard Similarity	Limited semantic understanding and small dataset
[2]	Alsaif et al. (2022)	Bidirectional recommendation between recruiters and job seekers	NER, semantic similarity, machine learning	Evaluated on limited data and lacks large-scale validation
[4]	Sinha et al. (2021)	Review NLP and ML-based resume screening techniques	Systematic literature review	Mostly descriptive; limited implementation insights
[10]	Harsha et al. (2022)	Develop an automated resume screening application	SpaCy-based NLP and candidate scoring	Limited evaluation and no multilingual support
[16]	Roy et al. (2020)	Automate resume recommendation using machine	Machine learning-based recommendation system	Dataset details and benchmarking are limited

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The studies summarized in Table 1 highlight the growing role of NLP and machine learning in recruitment automation. Saatçı et al. [1] proposed an NLP-based resume screening framework using Named Entity Recognition and Jaccard similarity for candidate ranking. Alsaif et al. [2] introduced a bidirectional recommendation system that improves matching between job seekers and recruiters through semantic analysis.

Sinha et al. [4] reviewed existing NLP and machine learning techniques for resume screening and emphasized the need for context-aware recruitment systems. Harsha et al. [10] developed a practical resume screening application using SpaCy-based NLP techniques, while Roy et al. [16] applied machine learning for automated resume recommendation and candidate selection.

Overall, the reviewed studies demonstrate that NLP and machine learning can significantly improve recruitment efficiency and candidate matching. However, challenges such as limited semantic understanding, small datasets, explainability, and scalability remain important research issues that require further investigation [1], [2], [4], [10], [16].

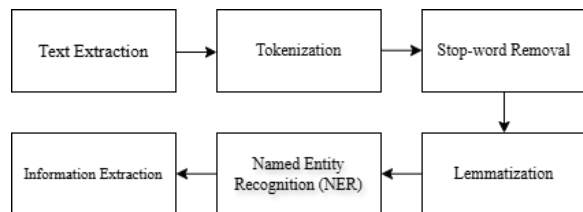


Figure 2. NLP Processing Flowchart

### III. ANALYSIS OF EXISTING APPROACHES

The reviewed studies demonstrate the growing adoption of Artificial Intelligence, Machine Learning, and Natural Language Processing techniques in recruitment automation. Earlier approaches primarily relied on keyword matching and rule-based filtering mechanisms to identify suitable candidates. Although these methods reduced manual effort, they often failed to capture semantic relationships between candidate skills and job requirements, leading to inaccurate matching results [1], [5], [15].

Recent research has shifted toward NLP-driven resume screening systems that utilize text preprocessing, Named Entity Recognition (NER), and similarity-based matching techniques. Saatçı et al. [1] employed NLP preprocessing and Jaccard similarity to rank candidates, while Alsaif et al. [2] introduced a bidirectional recommendation framework capable of matching both job seekers and recruiters. These approaches demonstrated improved automation and matching efficiency compared to traditional screening methods. Recent studies have further enhanced matching accuracy through transformer-based semantic representations and BERT-powered screening systems [23], [24], [27].

Several studies have also incorporated machine learning techniques to enhance candidate classification and recommendation accuracy. Pimpalkar et al. [3], Sajid et al. [9], and Ali et al. [13] explored machine learning-based resume analysis frameworks that automate candidate evaluation through structured information extraction and classification. Such systems reduce recruiter workload and improve consistency in decision-making. However, many of these approaches rely on limited datasets and lack comprehensive performance evaluation. Recent AI-driven ranking and recommendation systems have attempted to address these limitations through advanced learning models and intelligent candidate ranking mechanisms [26], [33].

Another important trend is the use of semantic analysis and contextual language understanding. Recent studies suggest that advanced NLP models can better identify relationships between candidate competencies and job requirements compared to conventional keyword-based approaches [11], [12]. Furthermore, transformer-based classifiers, Large Language Models, and human-LLM collaborative matching frameworks have demonstrated promising results in resume classification and recruitment decision support [28], [29], [30]. Nevertheless, the integration of transformer-based architectures and Large Language Models in recruitment systems remains relatively limited, indicating significant opportunities for future research.

Overall, the comparative analysis reveals that modern NLP-based approaches outperform traditional manual and keyword-driven screening methods in terms of efficiency, scalability, and matching capability. However, challenges related to semantic understanding, fairness, explainability, and benchmark evaluation datasets continue to limit the effectiveness of existing systems [4], [11], [12], [21], [35]. Addressing these challenges is essential for developing more intelligent and reliable recruitment solutions.

#### IV. RESEARCH GAPS

The literature review and comparative analysis reveal several important research gaps that continue to limit the effectiveness of existing automated resume screening and job recommendation systems.

##### *A. Limited Semantic Understanding*

Most existing systems rely heavily on keyword matching, Jaccard similarity, cosine similarity, or rule-based extraction techniques for candidate-job matching [1], [8], [15]. While these approaches are computationally efficient, they often fail to capture contextual meaning, semantic relationships, and transferable skills expressed using different terminology. Consequently, qualified candidates may be overlooked simply because their resumes use alternative wording compared to job descriptions [1], [4]. Recent studies utilizing Sentence-BERT, BERT, and transformer-based matching approaches have demonstrated improvements in semantic understanding; however, their adoption remains limited across recruitment systems [23], [24], [27].

##### *B. Small and Non-Standardized Datasets*

A significant limitation observed across the reviewed studies is the use of small and domain-specific datasets for evaluation [2], [9], [10]. Many researchers conduct experiments using limited numbers of resumes and job descriptions, making it difficult to assess the generalizability of proposed models. Furthermore, the absence of publicly available benchmark datasets restricts direct comparison among different approaches and hinders reproducibility [2], [6]. Similar limitations have also been reported in recent AI-driven resume ranking and classification studies [26], [33].

##### *C. Lack of Fairness and Bias Evaluation*

Although automated recruitment systems are often promoted as mechanisms for reducing human bias, few studies explicitly evaluate fairness-related metrics [11], [12]. Existing approaches rarely examine whether algorithmic decisions disproportionately affect candidates based on gender, ethnicity, educational background, or other demographic factors. Consequently, fairness-aware recruitment remains an important and underexplored research area [11], [21], [35].

##### *D. Underutilization of Advanced NLP Models*

Recent advancements in transformer architectures and Large Language Models have demonstrated remarkable capabilities in semantic understanding and contextual reasoning. However, their adoption within resume screening systems remains limited [11], [12]. Most existing solutions continue to rely on traditional NLP pipelines and shallow similarity measures rather than leveraging modern language representations. Emerging research on transformer-based classification, LLM-powered screening, and AI-assisted recruitment demonstrates significant potential for improving candidate-job matching accuracy [24], [28], [29], [30].

##### *E. Scalability and Deployment Challenges*

Another important research gap identified from the reviewed literature is the limited focus on scalability and real-world deployment considerations. Most existing studies evaluate their proposed systems using relatively small datasets under controlled experimental conditions [1], [2], [9]. While these evaluations demonstrate the feasibility of automated resume screening, they do not adequately reflect the complexity of large-scale recruitment environments where thousands of resumes may be processed daily across multiple job domains and organizational requirements.

In practical recruitment scenarios, systems must efficiently handle diverse resume formats, varying document structures, incomplete candidate information, and continuously changing job descriptions. Furthermore, organizations increasingly require integration with Applicant Tracking Systems (ATS), Human Resource Management Systems (HRMS), and cloud-based recruitment platforms.

However, only a limited number of studies discuss system interoperability, deployment architecture, or computational efficiency during large-scale operation [8], [10], [19], [34].

Another challenge relates to maintaining model performance over time. As job market requirements evolve and new technical skills emerge, recruitment models require periodic updates and retraining to ensure continued relevance and accuracy. Existing literature provides limited discussion regarding model maintenance, continuous learning mechanisms, and adaptation to changing industry demands [11], [20], [29]. Therefore, future research should focus not only on improving matching accuracy but also on developing scalable, adaptive, and deployment-ready recruitment systems capable of supporting real-world organizational hiring processes.

## V. SURVEY METHODOLOGY

This survey follows a systematic literature review methodology to identify, analyze, and compare existing research related to automated resume screening and job recommendation systems using Natural Language Processing. The objective was to provide a comprehensive overview of current approaches, identify research trends, and uncover existing limitations within the field [4], [6].

Relevant studies were collected from major academic databases, including IEEE Xplore, SpringerLink, ACM Digital Library, Google Scholar, ScienceDirect, and MDPI. Search queries included combinations of keywords such as “resume screening,” “resume parsing,” “job recommendation,” “candidate ranking,” “recruitment automation,” “Natural Language Processing,” and “Artificial Intelligence in recruitment” [1], [2], [4].

To ensure systematic literature retrieval, a Boolean search strategy was adopted. A representative search string used during the review process was:

("resume screening" OR "resume parsing" OR "candidate screening")

AND

("NLP" OR "natural language processing")

AND

("job recommendation" OR "candidate ranking" OR "recruitment system")

The initial search yielded more than fifty publications. After removing duplicates and irrelevant studies, twenty highly relevant papers were shortlisted for detailed examination. Selection criteria included publication quality, relevance to resume screening or job recommendation, methodological clarity, availability of experimental results, and publication date between 2018 and 2026 [2], [4], [6]. From the shortlisted studies, ten representative papers were selected for detailed analysis in the literature review section. Information extracted from each study included research objectives, methodologies, datasets, evaluation techniques, reported limitations, and future research directions. Comparative analysis was subsequently performed to identify common patterns, strengths, weaknesses, and research opportunities across the literature [1]–[10].

The systematic approach adopted in this survey ensures that the findings are based on a diverse and representative sample of recent research contributions in AI-driven recruitment systems [4], [6], [11].

## VI. PROPOSED CONCEPTUAL FRAMEWORK

Based on the limitations identified in existing literature, a conceptual framework is proposed for developing an advanced Automated Resume Screening and Job Recommendation System using Natural Language Processing. The proposed framework aims to improve semantic understanding, recommendation accuracy, fairness, explainability, and scalability while addressing shortcomings observed in existing recruitment systems [1], [2], [11], [21], [35].

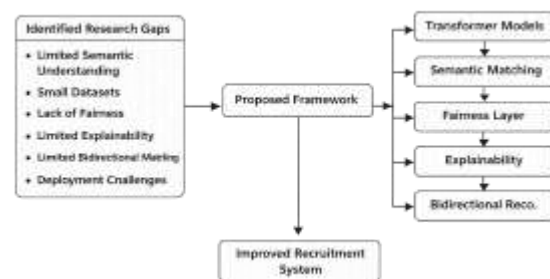


Figure 3. Proposed Conceptual Framework

The proposed system consists of four major stages: data acquisition, NLP-based information extraction, semantic matching, and intelligent recommendation. Initially, resumes and job descriptions are collected and preprocessed through text cleaning, tokenization, stop-word removal, and lemmatization. These preprocessing techniques help convert unstructured textual information into a structured format suitable for further analysis [1], [7], [9], [25].

In the second stage, Named Entity Recognition (NER) techniques are applied to identify and extract important entities such as technical skills, educational qualifications, certifications, work experience, and professional competencies. Existing studies have demonstrated the effectiveness of NER-based extraction for recruitment-related applications; however, many systems rely on traditional rule-based approaches that limit scalability and semantic understanding [2], [8], [9], [22]. Therefore, the proposed framework incorporates modern NLP techniques to improve extraction accuracy and contextual awareness.

The third stage focuses on semantic matching between candidate profiles and job requirements. Unlike conventional keyword-based systems that depend on exact word matching, the proposed framework utilizes transformer-based language models such as BERT, Sentence-BERT (SBERT), and other contextual embedding techniques to generate semantic representations of resumes and job descriptions [23], [24], [27]. Similarity scores are then computed using vector-based comparison methods to determine candidate-job compatibility more effectively than traditional Jaccard or cosine similarity approaches [1], [15], [28].

The recommendation stage generates personalized job recommendations for candidates and candidate recommendations for recruiters. Inspired by bidirectional recommendation approaches proposed in recent literature, the framework supports reciprocal matching by simultaneously considering recruiter requirements and candidate preferences [2], [16], [31]. This two-sided recommendation mechanism is expected to improve overall recruitment efficiency and user satisfaction.

To address fairness concerns identified in existing studies, fairness-aware ranking mechanisms will be incorporated into the recommendation process. Evaluation metrics such as demographic parity and equal opportunity may be considered to ensure that recommendations remain unbiased and transparent [11], [12], [21], [35]. Additionally, explainability features can be integrated to provide recruiters and candidates with interpretable reasons behind recommendation decisions [12], [30].

The proposed framework also considers emerging developments in Large Language Models and AI-assisted recruitment systems. Recent studies have demonstrated that transformer-based architectures and LLM-powered screening approaches can improve candidate ranking accuracy, contextual understanding, and decision support capabilities [11], [24], [29], [30], [34]. Integrating such technologies can significantly enhance recruitment effectiveness while maintaining transparency and fairness.

The framework can be implemented using Python-based technologies, including SpaCy, Hugging Face Transformers, Scikit-learn, and Streamlit. These tools provide robust support for NLP preprocessing, machine learning integration, semantic analysis, and interactive web-based deployment [1], [8], [10], [26]. Overall, the proposed framework aims to bridge existing research gaps by combining advanced NLP techniques, semantic matching, fairness-aware evaluation, explainability mechanisms, and bidirectional recommendation capabilities within a unified recruitment platform [2], [11], [12], [21], [35].

## VII. CONCLUSION

Automated Resume Screening and Job Recommendation Systems have emerged as promising applications of Artificial Intelligence and Natural Language Processing within modern recruitment processes. The increasing volume of job applications and the need for efficient candidate evaluation have motivated researchers to develop intelligent systems capable of automating resume parsing, candidate ranking, and recommendation tasks [1], [2], [4], [21].

This survey reviewed recent research contributions published between 2018 and 2026, focusing on NLP-based resume screening, machine learning-driven candidate selection, recommendation systems, and AI-assisted recruitment frameworks. A detailed literature review and comparative analysis revealed that existing approaches successfully reduce manual effort and improve recruitment efficiency through techniques such as Named Entity Recognition, similarity-based matching, resume parsing frameworks, machine learning models, and AI-driven ranking systems [1]–[10], [22], [26], [33]. However, several limitations continue to persist, including reliance on keyword-based matching, lack of semantic understanding, limited evaluation datasets, insufficient fairness assessment, and inadequate explainability mechanisms [1], [4], [11], [21], [35]. The survey further identified important research gaps related to semantic candidate-job matching, fairness-aware recruitment, explainable AI, benchmark dataset availability, and integration of modern transformer-based language models [11], [12]. These findings suggest that future recruitment systems should move beyond traditional similarity measures and incorporate advanced contextual language understanding techniques capable of capturing deeper relationships between candidate competencies and job requirements. Recent studies based on Sentence-BERT, BERT, transformer architectures, and Large Language Models further support this direction by demonstrating improved semantic matching and candidate evaluation capabilities [23], [24], [28], [29], [30].

To address these challenges, a conceptual framework was proposed that integrates NLP preprocessing, Named Entity Recognition, transformer-based semantic matching, bidirectional recommendation, and fairness-aware evaluation mechanisms. The proposed approach aims to improve recruitment accuracy, transparency, and decision quality while supporting both recruiters and job seekers more effectively [2], [11], [12], [31], [32].

In conclusion, AI-powered recruitment systems represent a rapidly evolving research domain with significant practical potential. Continued advancements in NLP, machine learning, transformer-based models, Large Language Models,

and explainable AI are expected to play a crucial role in shaping next-generation recruitment platforms that are not only efficient and accurate but also fair, transparent, scalable, and adaptable to real-world hiring requirements [11], [12], [20], [24], [29], [30], [34], [35].

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