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A Comparative Survey of Traditional and AI-Based Resume Screening and Recruitment Systems

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Abstract: In recent years the recruitment process has changed significantly because organizations receive very large numbers of job applications through online platforms making manual resume screening difficult and time consuming. To handle this problem many companies use Applicant Tracking Systems (ATS) that automatically filter resumes using keyword-based techniques. Although these systems reduce manual effort and improve processing speed they often fail to understand the actual meaning and context of resumes which can lead to rejection of qualified candidates because of different wording or resume formats. To overcome these limitations researchers introduced Artificial Intelligence (AI), Natural Language Processing (NLP), Machine Learning (ML) and transformer-based models into recruitment systems for better semantic analysis and candidate evaluation. Recent developments in Large Language Models (LLMs) such as BERT, GPT, LLaMA and Mixtral have further improved contextual understanding and resume job matching accuracy. This survey paper presents a comparative study of traditional and AI based resume screening and recruitment systems. The paper reviews keyword based ATS, NLP driven approaches, transformer architectures and LLM based recruitment models. It compares these systems based on contextual understanding, matching accuracy, scalability, recommendation capability and user experience. The survey also discusses major challenges in existing systems such as lack of personalization, fragmented career guidance, limited contextual analysis and bias in AI models. From the overall analysis it is observed that AI driven recruitment systems provide more accurate and intelligent candidate evaluation compared to traditional methods and systems.

Index Terms **-** Component, Artificial Intelligence (AI), Resume Screening, Recruitment Systems, Applicant Tracking Systems (ATS), Natural Language Processing (NLP), Large Language Models (LLMs), Resume Analysis, Job Matching, Semantic Analysis, Machine Learning (ML), Transformer Models, Career Guidance Systems.

I. INTRODUCTION

In today's digital era the recruitment process has become more complex because organizations receive very large numbers of job applications through online platforms. Manual screening of resumes is difficult time consuming and sometimes inefficient when companies need to process hundreds or thousands of resumes for a single job role. To reduce manual effort and speed up hiring processes many organizations started using Applicant Tracking Systems (ATS). These systems automatically filter and shortlist resumes based on predefined rules and keyword matching techniques. Although ATS helps in handling large volumes of applications, traditional systems mainly focus on keyword based filtering and fail to understand the actual meaning and context of candidate profiles. Because of this many skilled candidates may get rejected if their resumes do not contain exact keywords mentioned in job descriptions.

To overcome these limitations researchers introduced Artificial Intelligence (AI), Natural Language Processing (NLP), and Machine Learning (ML) techniques into recruitment systems. NLP-based approaches help in extracting important information such as skills, education, certifications and work experience from resumes. Later transformer based architectures like BERT and GPT improved contextual understanding by analyzing semantic relationships between words and sentences. Recent advancements in Large Language Models (LLMs) such as LLaMA and Mixtral further enhanced resume analysis and job matching by providing deeper understanding of textual information and generating intelligent recommendations.

Even though modern AI based recruitment systems provide better accuracy and semantic understanding compared to traditional ATS many existing systems still focus only on specific tasks such as resume screening or job matching. Most platforms do not provide integrated support for skill gap identification, career guidance, placement preparation, and personalized recommendations. Users often need to depend on multiple separate platforms for resume building, preparation and career planning which reduces usability and efficiency.

This survey paper presents a comparative study of traditional and AI based resume screening and recruitment systems. The paper studies different approaches including keyword based ATS, NLP driven systems, transformer based architectures and LLM-based recruitment models. It also compares these systems based on factors such as contextual understanding, accuracy, scalability, recommendation capability and user experience. The survey further highlights major challenges, research gaps and future directions in intelligent recruitment systems. The overall aim of this paper is to provide a clear understanding of how recruitment technologies have evolved and why more integrated and user focused AI driven systems are needed in modern recruitment processes.

II. SCOPE OF SURVEY

This survey paper mainly focuses on studying the evolution of resume screening and recruitment systems from traditional Applicant Tracking Systems (ATS) to modern Artificial Intelligence (AI) based recruitment technologies. The survey covers different approaches used for resume analysis, candidate shortlisting, job matching and recommendation generation. It aims to understand how recruitment technologies have improved over time and how modern AI techniques are changing the recruitment process.

The survey includes traditional ATS systems that mainly use keyword based filtering methods for screening resumes. It also studies Natural Language Processing (NLP) based systems which extract important information such as skills, education and experience from resumes using text processing techniques. In addition the survey covers transformer based architectures and Large Language Models (LLMs) such as BERT, GPT, LLaMA, and Mixtral, which provide better semantic understanding and contextual analysis for recruitment tasks.

The paper also focuses on comparing these systems on the basis of important parameters such as contextual understanding, matching accuracy, scalability, recommendation capability, response time and user experience. Along with technical analysis the survey studies features like skill gap identification, personalized recommendations, placement preparation support and career guidance provided by modern AI-driven systems.

This survey mainly focuses on recent developments in AI based recruitment technologies and intelligent resume analysis systems. However it does not include detailed coding implementation, algorithm optimization, or domain specific recruitment systems limited to only one industry. The main objective of this survey is to identify the strengths, limitations, research gaps and future directions of existing recruitment systems and highlight the need for more integrated and user focused AI driven career assistance platforms.

III. METHODOLOGY

The methodology followed in this survey paper is based on systematic study and comparative analysis of existing resume screening and recruitment systems. The main objective of this methodology is to understand how recruitment technologies have evolved from traditional Applicant Tracking Systems

(ATS) to modern Artificial Intelligence (AI)-based systems and to identify their advantages, limitations, and research gaps.

To begin the survey, research papers, journal articles, conference publications, technical reports, and online academic resources were collected from reliable platforms such as Google Scholar, IEEE Xplore, Springer, and research databases. During the collection process, important keywords like resume screening, Applicant Tracking Systems (ATS), Artificial Intelligence in recruitment, Natural Language Processing (NLP), transformer models, Large Language Models (LLMs), semantic analysis, and job matching systems were used to find relevant studies related to the topic.

After collecting the research papers, a selection process was carried out to choose the most relevant and useful studies. Papers were selected based on factors such as relevance to recruitment systems, clarity of methodology, recent technological contribution, and usefulness in comparative analysis. More importance was given to recent AI-based approaches and systems using transformer architectures and LLMs because they represent current developments in intelligent recruitment technologies.

The selected studies were then grouped into different categories such as traditional ATS systems, NLP-based recruitment systems, transformer-based models, and LLM-based recruitment systems. This categorization helped in understanding the working principles and technological differences between different approaches. Each category was analyzed on the basis of important parameters such as contextual understanding, matching accuracy, semantic analysis capability, scalability, recommendation support, processing speed, and user experience.

Finally, a comparative analysis of all systems was performed to identify common challenges and research gaps in existing recruitment technologies. Special attention was given to issues such as lack of contextual understanding, fragmented career guidance systems, limited personalization, and absence of integrated placement preparation support. Based on this analysis, future directions and the need for more intelligent and user-focused recruitment systems were identified.

IV. LITERATURE REVIEW

The recruitment and resume screening process has evolved significantly over the years due to the advancement of Artificial Intelligence (AI), Natural Language Processing (NLP), and machine learning technologies. Earlier recruitment systems mainly depended on manual resume screening which required high human effort and time. Later organizations started using automated systems to improve recruitment speed and efficiency. Researchers proposed different approaches such as keyword based Applicant Tracking Systems (ATS), NLP based resume analysis systems, transformer based architectures and Large Language Models (LLMs) for improving candidate evaluation and job matching accuracy. This section discusses the major recruitment systems and technologies proposed by different researchers along with their advantages and limitations.

1. *Traditional Applicant Tracking Systems (ATS)*

One of the earliest automated recruitment approaches was the use of Applicant Tracking Systems (ATS). R. Girardi in the paper “Applicant Tracking Systems and the Modern Recruitment Process” [8] explained how ATS systems are widely used for automatic resume filtering and candidate shortlisting. These systems mainly use keyword based matching techniques where resumes are scanned for predefined keywords related to job descriptions.

Traditional ATS systems helped organizations process large numbers of resumes quickly and reduced manual screening effort. However these systems had major limitations because they could not understand semantic meaning or contextual relationships between skills and job requirements. Due to this many qualified candidates were rejected if their resumes did not contain exact keywords required by the system.

2. *NLP-Based Recruitment Systems*

To overcome the limitations of keyword based ATS systems, researchers introduced Natural Language Processing (NLP) techniques into recruitment systems. D. Jurafsky and J. H. Martin in “Speech and Language Processing” [1] discussed different NLP techniques such as tokenization, semantic analysis, information extraction and text classification which are useful for textual analysis systems. Similarly S. Bird, E. Klein, and E. Loper in “Natural Language Processing with Python” [2] explained practical NLP methods for processing and analyzing textual data.

Later S. Malherbe and T. Groves in the research paper “Resume Parsing and Candidate Classification using NLP and Machine Learning” [9] proposed NLP and machine learning techniques for extracting information from resumes and improving candidate classification. These systems improved resume parsing, skill extraction, and structured information analysis compared to traditional ATS systems. However NLP based systems still depended heavily on manual feature engineering and had limited ability to understand deeper semantic meaning in complex recruitment scenarios.

3. Transformer Based Recruitment Systems

A major improvement in recruitment technologies came with the introduction of transformer based architectures. A. Vaswani et al. proposed the transformer model in the paper “Attention Is All You Need” [3]. This research introduced the attention mechanism, which improved contextual understanding and semantic analysis in textual data processing.

After this J. Devlin et al. introduced BERT in the paper “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding” [4]. BERT improved resume job matching by understanding bidirectional relationships between words and sentences. Transformer based systems were more effective than traditional NLP systems because they could identify contextual similarities even when exact keywords were not present. These systems significantly improved matching accuracy, semantic understanding and intelligent candidate evaluation.

4. *Large Language Model (LLM)-Based Systems*

Recent advancements in AI introduced Large Language Models (LLMs) for intelligent recruitment systems. T. Brown et al. proposed GPT models in the paper “Language Models are Few-Shot Learners” [5], which improved semantic understanding and human like text generation. Later H. Touvron et al. proposed LLaMA in “LLaMA: Open and Efficient Foundation Language Models” [6], which provided efficient transformer based language models for AI applications. Mistral AI also introduced Mixtral in the technical report “Mixtral of Experts” [7], which improved reasoning and contextual understanding capabilities.

LLM based systems are capable of deep semantic analysis, intelligent recommendation generation, skill gap identification and real time feedback. These systems provide much better contextual understanding compared to traditional ATS and NLP-based systems. However challenges such as high computational cost, bias in AI models and lack of explainability still exist in many AI-driven recruitment systems.

5. *Recommendation and Career Guidance Systems*

Researchers also studied recommendation systems and adaptive learning approaches for career support and personalized guidance. F. Ricci, L. Rokach, and B. Shapira in “Recommender Systems Handbook” [10] discussed recommendation techniques used for personalized suggestions and intelligent decision making systems. Similarly, P. Brusilovsky and E. Millán in “User Models for Adaptive Hypermedia and Adaptive Educational Systems” [18] explained adaptive learning methods and personalized educational systems that support career preparation and learning guidance.

These systems improved personalized recommendations and learning support but many platforms still work separately and do not provide integrated solutions combining resume analysis, placement preparation, and career guidance in a single system.

From the literature review, it is observed that recruitment technologies have evolved from simple keyword-based ATS systems to advanced AI driven semantic analysis models. Modern AI based systems provide better contextual understanding, semantic analysis and intelligent recommendations compared to traditional recruitment systems. However many existing systems still lack integrated placement preparation support, personalized career guidance, transparency and scalability which highlights the need for more intelligent and user focused recruitment platforms.

V. COMPARATIVE ANALYSIS

Different researchers have proposed various approaches for improving resume screening and recruitment systems. Earlier research mainly focused on keyword based filtering systems while recent studies introduced NLP, transformer architectures and Large Language Models (LLMs) for better contextual understanding and intelligent candidate evaluation. This section compares different research papers based on their approach, technologies used, advantages and limitations.

R. Girardi [8] discussed traditional Applicant Tracking Systems (ATS) that use keyword-based filtering methods for resume screening. The paper mainly focused on improving recruitment speed and reducing manual effort in handling large numbers of resumes. Although the system was effective for automatic filtering the research highlighted that ATS systems fail to understand contextual meaning and semantic relationships between resumes and job descriptions. This limitation often leads to rejection of qualified candidates due to missing keywords.

D. Jurafsky and J. H. Martin [1], along with S. Bird, E. Klein, and E. Loper [2] focused on Natural Language Processing (NLP) techniques for textual analysis and information extraction. Their research explained methods such as tokenization, semantic analysis, text classification and Named Entity Recognition (NER). Compared to traditional ATS systems these approaches improved resume parsing and structured information extraction. However these studies mainly concentrated on NLP concepts and required significant manual feature engineering for practical recruitment applications.

S. Malherbe and T. Groves [9] proposed a recruitment system based on NLP and machine learning techniques for resume parsing and candidate classification. Their paper improved candidate evaluation accuracy compared to keyword based systems by extracting structured information from resumes. The study showed better text processing and classification performance but the system still had limitations in understanding deeper semantic meaning and complex contextual relationships between candidate profiles and job requirements.

A major advancement was introduced by A. Vaswani et al. [3] through the transformer architecture proposed in the paper "Attention Is All You Need." This research improved contextual understanding using attention mechanisms and became the foundation for modern NLP systems. Later, J. Devlin et al. [4] introduced BERT, which improved bidirectional contextual understanding and semantic analysis. Compared to previous NLP based approaches transformer-based models provided better resume-job matching accuracy and contextual interpretation. However these models required high computational resources and large datasets for training.

T. Brown et al. [5] further improved language understanding through GPT models capable of few-shot learning and human like text generation. Similarly H. Touvron et al. [6] proposed LLaMA, while Mistral AI [7] introduced Mixtral for efficient AI-based semantic analysis and reasoning. These papers demonstrated significant improvements in contextual understanding, intelligent recommendation generation and semantic matching capabilities compared to traditional and NLP based systems. However challenges such as computational cost, model bias, lack of explainability and dependency on high quality training data were still observed.

F. Ricci, L. Rokach, and B. Shapira [10] discussed recommendation systems for personalized suggestions while P. Brusilovsky and E. Millán [18] focused on adaptive learning and personalized educational systems. These studies contributed towards career guidance and recommendation support but they mainly focused on recommendation methodologies instead of integrated recruitment platforms.

From the comparative analysis of different research papers it is observed that recruitment technologies have gradually evolved from keyword based filtering systems to advanced AI driven semantic analysis models. Traditional ATS systems improved recruitment speed but lacked contextual understanding. NLP based approaches improved text processing and information extraction while transformer and LLM based models provided better semantic analysis, intelligent recommendations and contextual matching. However many existing research works still focus on specific tasks such as resume screening, recommendation generation or learning support separately. Very few studies provide an integrated solution that combines resume analysis, job matching, skill gap identification, career guidance and placement preparation within a single intelligent platform.

Table 5.1: Comparative Analysis of Papers

Author/Paper	Approach Used	Main Contribution	Advantages	Limitations
R. Girardi - Applicant Tracking Systems and the Modern Recruitment Process	Keyword Based ATS	Automatic resume filtering and shortlisting	Fast processing of resumes helps reduce manual effort	Cannot understand semantic meaning, high rejection rate
D. Jurafsky and J. H. Martin - Speech and Language Processing	NLP Techniques	Text processing and semantic analysis methods	Better text understanding and information extraction	Mainly theoretical, requires feature engineering
S. Bird, E. Klein and E. Loper - Natural Language Processing with Python	NLP based Processing	Practical NLP methods for textual analysis	Improved resume parsing and structured data extraction	Limited deep contextual understanding
S. Malherbe and T. Groves - Resume Parsing and Candidate Classification using NLP and Machine Learning	NLP + Machine Learning	Resume parsing and candidate classification	Better candidate evaluation than ATS systems	Limited semantic understanding and scalability
A. Vaswani et al. - Attention Is All You Need	Transformer Architecture	Introduced attention mechanism for contextual understanding	Improved semantic analysis and contextual relationships	High computational requirements
J. Devlin et al. - BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	BERT Transformer Model	Bidirectional contextual understanding	Better resume job matching accuracy	Requires large training datasets and resources
T. Brown et al. - Language Models are Few-Shot Learners	GPT based LLM	Human like text generation and semantic analysis	Strong contextual understanding and intelligent recommendations	Expensive computational infrastructure
H. Touvron et al. - LLaMA: Open and Efficient Foundation Language Models	LLM based Semantic Analysis	Efficient transformer based AI model	Improved reasoning and semantic matching	Model bias and explainability issues
Mistral AI - Mixtral of Experts	Advanced LLM Architecture	Efficient AI reasoning and contextual analysis	Better semantic understanding and faster inference	High dependency on quality training data
F. Ricci, L. Rokach, and B. Shapira - Recommender Systems Handbook	Recommendation Systems	Personalized recommendation techniques	Better personalized suggestions	Not focused directly on recruitment systems
P. Brusilovsky and E. Millán - Adaptive Educational Systems	Adaptive Learning Systems	Personalized learning and career guidance	Supports adaptive recommendations and learning paths	Limited integration with recruitment platform

VI. CHALLENGES IN EXISTING SYSTEMS

After studying different traditional and AI based recruitment systems several common challenges and limitations were identified. Although modern technologies improved recruitment accuracy and automation many existing systems still face problems related to contextual understanding, personalization, scalability and user guidance.

1. Lack of Contextual Understanding

Traditional Applicant Tracking Systems (ATS) mainly depend on keyword based filtering techniques. These systems cannot properly understand the actual meaning and context of resumes and job descriptions. Because of this candidates with relevant skills may get rejected if their resumes do not contain exact keywords required by the system.

2. Over Dependence on Keyword Matching

Many existing recruitment systems focus more on exact keyword matching rather than overall candidate capability. Candidates often modify resumes artificially to include specific keywords for passing ATS filters. This reduces fairness and affects the quality of recruitment decisions.

3. Limited Semantic Analysis

Although NLP based systems improved text processing and information extraction, many systems still struggle to understand deeper semantic relationships between skills, experience and job roles. These systems often fail in handling complex resume structures and contextual variations

4. High Computational Requirements

Transformer based models and Large Language Models (LLMs) provide better contextual understanding but they require high computational resources, large datasets and expensive infrastructure. This increases operational cost and makes large scale deployment difficult for many organizations

5. Lack of Explainability and Transparency

Many AI driven recruitment systems work like black box models where users do not understand how scores and recommendations are generated. Lack of transparency reduces trust in the system and creates difficulty in validating recruitment decisions.

6. Bias in AI Models

AI based systems can inherit bias from training data. Factors related to education, resume formatting, keywords or experience may influence system decisions unfairly. This can create ethical and fairness related issues in recruitment processes.

7. Fragmented Recruitment and Career Guidance Platforms

Most existing systems focus only on one specific task such as resume screening, job matching or recommendation generation. Users often need multiple separate platforms for resume building, skill improvement, placement preparation and career guidance which reduces usability and efficiency.

8. Limited Personalized Recommendations

Many systems only provide general suggestions or matching scores. Personalized career guidance, adaptive learning support and skill gap identification are still limited in many recruitment platforms. Users often do not get clear direction on how to improve their profiles.

9. Scalability Issues

Some traditional and NLP based systems face scalability problems when processing very large datasets or handling multiple users simultaneously. Slow response time and reduced performance affect user experience in large scale recruitment scenarios.

10. Poor Real Time Interaction and Feedback

Several existing recruitment systems do not provide interactive or real time feedback to users. Candidates are often unable to understand their weakness immediately or improve their resumes continuously based on intelligent suggestions.

From these challenges it is observed that although recruitment technologies have improved significantly, there is still need for more intelligent, transparent, scalable and user focused systems that combine resume analysis, semantic job matching, career guidance and placement preparation within a single integrated platform.

VII. RESEARCH GAPS

During the survey and comparative analysis of different research papers and existing recruitment systems several important research gaps were identified. Although many researchers have proposed systems for resume screening, job matching and candidate evaluation most existing approaches still have multiple limitations related to contextual understanding, personalization, integration and intelligent career support.

One major research gap observed in traditional Applicant Tracking Systems (ATS) is the over-dependence on keyword based filtering techniques. Most ATS systems discussed in earlier research papers focus mainly on matching predefined keywords between resumes and job descriptions. These systems improve recruitment speed but fail to understand semantic meaning and contextual relationships between candidate skills and job requirements. Because of this many skilled candidates may get rejected even if they are suitable for the role. Existing research papers also show limited focus on intelligent semantic analysis and adaptive candidate evaluation in traditional recruitment systems.

Another important gap identified during the survey is the limited contextual understanding in many NLP based recruitment systems. Although NLP approaches improved resume parsing and information extraction several research papers mainly focused on text processing techniques such as tokenization, classification and Named Entity Recognition (NER). Most systems still require manual feature engineering and struggle to capture deeper semantic relationships between resumes and job descriptions. The surveyed papers also showed that many NLP based systems are difficult to generalize across different job domains and changing recruitment requirements.

The survey also found that transformer based and LLM based recruitment systems provide better semantic analysis and contextual understanding compared to earlier methods. However many research papers mainly focus on improving resume job matching accuracy and recommendation generation only. Very few systems provide integrated support for skill gap analysis, placement preparation, adaptive learning and career guidance within a single platform. Most existing platforms work separately for resume analysis, interview preparation or recommendation systems which reduces usability and overall user experience.

Another major research gap observed is related to explainability and transparency in AI driven recruitment systems. Many modern AI models work as black box systems where users cannot clearly understand how recommendations or scores are generated. Research papers also show limited work on reducing bias in AI based recruitment models and ensuring fairness in candidate evaluation.

Scalability and real time processing were also identified as important gaps during the survey. Several systems require high computational resources and expensive infrastructure for deployment, especially transformer and LLM based models. Many research papers focus more on model performance and less on scalability, deployment efficiency and practical usability in large scale recruitment environments.

From the overall survey it is observed that there is still lack of a unified and intelligent recruitment platform that combines resume analysis, semantic job matching, personalized recommendations, skill gap identification, placement preparation, adaptive learning support and transparent AI based decision making within a single system. These research gaps highlight the need for more scalable, explainable and user focused AI driven recruitment and career guidance platforms in future research.

VIII. FUTURE DIRECTIONS

1. Development of Integrated Recruitment Platforms

Future systems can combine resume analysis, job matching, placement preparation, career guidance and recommendation systems within a single platform. This can improve usability and provide complete support for candidates during recruitment processes.

2. Improved Semantic and Contextual Understanding

Future research can focus on improving semantic analysis and contextual understanding using advanced transformer architectures and Large Language Models (LLMs). This can help systems understand resumes and job descriptions more accurately.

3. Explainable Artificial Intelligence (XAI)

Many AI based recruitment systems work like black box models. Future systems should provide proper explanation for scores, recommendations and candidate evaluations so users can understand how decisions are generated.

4. Bias Reduction and Ethical AI

Future research should focus on reducing bias in AI driven recruitment systems. Systems should ensure fair candidate evaluation and avoid discrimination based on resume formatting, education background or keywords.

5. Personalized Career Guidance and Adaptive Learning

Future recruitment platforms can provide personalized learning paths, placement preparation plans, interview practice and skill development recommendations based on user profiles and performance.

6. Integration with Real Time Job Portals

Future systems can connect with professional networking platforms and job portals such as LinkedIn to provide real time job recommendations, trending skills and industry requirements.

7. Scalable and Efficient AI Models

Future research can focus on lightweight AI models, cloud based deployment and distributed architectures to improve scalability, reduce infrastructure cost and support large scale recruitment environments.

8. Multi Modal Candidate Evaluation

Future recruitment systems can analyze portfolios, GitHub profiles, certifications, coding profiles and video interviews along with resumes for more accurate candidate evaluation.

9. Real Time Interactive Feedback Systems

Future systems can provide continuous and real time feedback for resume improvement, interview preparation and skill enhancement to help users improve their profiles dynamically.

10. Continuous Learning and Self Improving Systems

AI driven recruitment systems can be designed to continuously learn from user interactions, hiring trends and recruitment outcomes to improve recommendation accuracy and system performance over time.

11. Multilingual Recruitment Support

Future systems can support multiple languages for resume analysis and job matching so that users from different regions and language backgrounds can use recruitment platforms more effectively.

12. Better Data Privacy and Security

Future research should also focus on secure data handling, privacy protection and ethical management of user information in AI driven recruitment and career guidance systems.

IX. CONCLUSION

This survey paper presented a comparative study of traditional and AI based resume screening and recruitment systems. The study analyzed different approaches proposed by researchers including keyword based Applicant Tracking Systems (ATS), Natural Language Processing (NLP) based systems, transformer architectures and Large Language Model (LLM) based recruitment systems. From the survey it was observed that traditional ATS systems improved recruitment speed and reduced manual effort but they lacked contextual understanding and semantic analysis capabilities. Because of this many qualified candidates could get rejected due to differences in keywords or resume formatting.

The survey also showed that NLP based systems improved resume parsing and information extraction by using techniques such as tokenization, text classification and semantic analysis. Later transformer based models and LLMs such as BERT, GPT, LLaMA and Mixtral significantly improved contextual understanding, semantic matching and intelligent recommendation generation. These systems provided better accuracy and more meaningful candidate evaluation compared to traditional recruitment methods.

However the survey identified several challenges and research gaps in existing systems. Many current platforms still focus only on specific tasks such as resume screening or job matching and do not provide integrated support for skill gap analysis, placement preparation, career guidance and personalized learning. Issues such as lack of explainability, bias in AI models, high computational cost and scalability limitations are also still present in many AI driven recruitment systems.

Overall the survey concludes that AI based recruitment systems represent an important advancement in modern hiring technologies. Future research should focus on developing integrated, scalable, transparent and user focused recruitment platforms that combine intelligent resume analysis, adaptive learning, personalized recommendations and ethical AI driven decision making within a single system.

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