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AI-DRIVEN RESUME ANALYSIS AND PLACEMENT SUPPORT

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Abstract The rapid adoption of Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) has expanded the use of automated techniques for resume analysis, recruitment matching, job recommendation, skill development, and interview preparation. This paper presents a comprehensive review of existing research on AI-driven resume analysis and placement support across five interconnected research areas: resume intelligence; semantic matching and Applicant Tracking System (ATS) evaluation; career and skill development; Large Language Model (LLM) and conversational support; and interview intelligence. The reviewed studies employ traditional NLP and machine-learning techniques such as regular expressions (regex), keyword matching, Term Frequency–Inverse Document Frequency (TF-IDF), Bag-of-Words (BoW), Word to Vector (Word2Vec), cosine similarity, k-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression and fuzzy logic, together with Named Entity Recognition (NER), Bidirectional Encoder Representations from Transformers (BERT), Robustly Optimized BERT Pretraining Approach (RoBERTa), distilled Bidirectional Encoder Representations from Transformers (DistilBERT), attention-based neural networks, collaborative filtering, retrieval-augmented generation (RAG), and LLM-based architectures. The literature shows a methodological progression from lexical and rule-based processing toward contextual, semantic, and generative approaches, with several studies reporting strong task-specific performance. At the same time, the evidence remains functionally fragmented: resume parsing and matching are extensively studied, while ATS evaluation, skill-gap analysis, learning support, conversational assistance, and AI-based interview preparation are addressed by smaller and more specialized groups of studies. The review identifies an integration gap in the literature, together with limitations related to dataset diversity, evaluation comparability, changing job requirements, explainability, fairness, privacy, and real-world validation. The findings provide a consolidated view of current methods, reported outcomes, and research opportunities in AI-supported resume analysis and placement preparation.

Keywords: Artificial Intelligence, Machine Learning, Natural Language Processing, Resume Parsing, ATS, Semantic Matching, Skill-Gap Analysis, Job Recommendation, Large Language Models, Mock Interview, Placement Assistance.

I. INTRODUCTION

The recruitment and placement process requires effective analysis of candidate resumes to identify relevant qualifications, skills, and suitable job opportunities. Traditional manual screening can be time-consuming, particularly when recruiters need to evaluate large numbers of applications against specific job requirements. Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) have therefore been explored to automate resume parsing, candidate screening, ranking, and job matching. For example, Ganesan et al. [1] investigated transformer-based skill identification, while Deshmukh and Bendre [2] explored machine-learning techniques for resume analysis and ranking. Existing approaches have evolved from conventional techniques, such as keyword matching, regular expressions, and statistical text representations, toward contextual language models and generative AI. Resume-enhancement and Applicant Tracking System (ATS) evaluation techniques have also been investigated to improve resume alignment with job requirements [4]. Pant et al. [6] examined keyword-based screening methods, while Lo et al. [8] proposed a context-aware, explainable multi-agent framework using Large Language Models (LLMs). These developments demonstrate the growing diversity of techniques used in automated recruitment and candidate evaluation.

Research has also expanded beyond screening and matching to include career recommendation, skill-gap identification, and interview preparation. Ashrafi et al. [13] investigated resume-based career recommendation and personalized reskilling, while Sribharathi et al. [15] explored an integrated approach involving resume parsing, skill-gap analysis, and job matching. AI-based interview systems have further examined automated question generation and candidate feedback [18], [19]. However, these functions are frequently addressed through separate systems, limiting the continuity of support available throughout the placement preparation process.

Existing research on AI-driven resume analysis and placement support is examined by comparing the methodologies, applications, reported findings, and limitations of the selected studies. The literature is organized into five areas: resume

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intelligence; semantic matching and ATS evaluation; career and skill development; LLM and conversational support; and interview intelligence. The analysis identifies recurring methodological and functional gaps, particularly in integration, evaluation consistency, explainability, fairness, privacy, and real-world applicability. These findings highlight future research directions toward more integrated and reliable AI-supported placement systems.

II. BACKGROUND AND REVIEW SCOPE

A. Research Context

AI-supported recruitment has evolved from keyword-based and rule-based systems toward more sophisticated approaches for resume information extraction, candidate matching, and personalized placement support. Pant et al. [6] investigated keyword matching and regular expressions for resume screening, while Panda et al. [7] examined conventional machine-learning techniques for resume classification. More recent studies have explored automated skill extraction [1], resume parsing [3], semantic job matching [9], career recommendation [13], [14], and AI-assisted interview preparation [18], [19]. These developments demonstrate the application of AI across both recruiter-oriented and candidate-oriented tasks.

The reviewed studies also differ in their scope and functionality. Some focus on specific tasks, such as skill extraction [1] or resume screening [6], whereas others integrate resume parsing, skill-gap analysis, and job matching [15]. LLM-based approaches further extend these capabilities through contextual resume evaluation, explanation, and feedback [8], while AI-based interview platforms support question generation and candidate assessment [18], [19]. These differences highlight the value of a thematic review for identifying common methodologies, functional overlaps, and gaps in existing placement-support systems.

B. Review Scope

The existing studies explore the application of Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) in resume analysis, recruitment matching, career development, and placement preparation. The reviewed literature is organized into five interconnected areas: resume intelligence; semantic matching and Applicant Tracking System (ATS) evaluation; career and skill development; Large Language Model (LLM) and conversational support; and interview intelligence.

The review considers the methods used, primary applications, reported findings, and limitations of the studies. The methods represented include regular expressions, keyword matching, TF-IDF, Bag-of-Words, Word2Vec, cosine similarity, KNN, SVM, Logistic Regression, fuzzy logic, Named Entity Recognition (NER), BERT, RoBERTa, DistilBERT, attention-based neural networks, collaborative filtering, and LLM-based architectures. For example, Pant et al. [6] investigated keyword matching and regular expressions, while Lo et al. [8] explored an LLM-based multi-agent framework. The studies differ substantially in datasets, task definitions, labels, baselines, and evaluation protocols; therefore, reported accuracy, F1-score (the harmonic mean of precision and recall), ranking metrics, processing time, and user-satisfaction values are interpreted as study-specific findings rather than directly comparable benchmark results.

The review examines how existing research addresses automated resume understanding, candidate--job matching, ATS evaluation, career development, skill-gap analysis, learning support, conversational assistance, and interview preparation. Particular attention is given to the relationships and discontinuities among these functions and to methodological limitations that motivate future research. For instance, Sribharathi et al. [15] addressed resume parsing, skill-gap analysis, and job matching, while the interview-support studies [18], [19] focus on interview preparation.

C. Review Methodology

The review focuses on existing research related to AI-driven resume analysis, recruitment matching, job recommendation,skill development, and interview preparation. Each paper was examined with respect to its problem addressed, methodology,technologies employed, evaluation approach, reported findings, and identified limitations. The papers were subsequently grouped into thematic categories based on their dominant functional contribution. Because the present review is based on a predefined collection of 20 papers, it is not intended to represent an exhaustive systematic search of all available literature.

D. Research Questions

1. **RQ1**. What AI, NLP, and machine-learning techniques are used for resume parsing, screening, and candidate ranking?
2. **RQ2**. How do existing systems perform semantic resume-job matching and ATS-oriented scoring?
3. **RQ3**. How are skill-gap analysis, job recommendation, and personalized learning addressed in existing systems?
4. **RQ4**. How are Large Language Models (LLMs) and AI systems used for conversational assistance and interview preparation?
5. **RQ5**. What are the major methodological and functional gaps in existing research?
6. **RQ6**. What research directions are suggested by the collective findings of the reviewed studies?

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E. Analytical Framework

The reviewed literature was analyzed across four common dimensions: methodology, primary application, reported findings, and limitations. Methodology captures the principal NLP, machine-learning, transformer, recommendation, or LLM techniques used. Primary application identifies the placement-related task addressed, such as resume parsing, screening, ATS evaluation, job matching, career recommendation, skill-gap analysis, learning support, or interview preparation. Reported findings record the principal performance or functional outcomes described in the surveyed sources. Limitations identify missing capabilities, dataset or format constraints, dependence on particular methods, and broader issues such as privacy, bias, changing job requirements, or limited integration [8].

The studies were then organized into five thematic research areas. This thematic organization is intended to reveal both methodological evolution and functional fragmentation. A study may contribute to more than one area when its system contains multiple relevant capabilities, as demonstrated by integrated resume parsing, skill-gap analysis, and job matching [15], as well as AI-based interview preparation systems [18], [19]. The resulting synthesis is used to establish the research gap and to derive literature-grounded research implications and future directions.

III. TAXONOMY OF THE REVIEWED LITERATURE

Fig. 1 organizes the reviewed studies into five interconnected research areas according to the principal capabilities represented in the surveyed literature: (A) resume intelligence, (B) semantic matching and ATS, (C) career and skill development, (D) LLM and conversational support, and (E) interview intelligence. The categories are functional rather than mutually exclusive; individual studies may contribute to more than one area. This taxonomy provides the structure for the thematic review and the subsequent cross-study gap analysis.

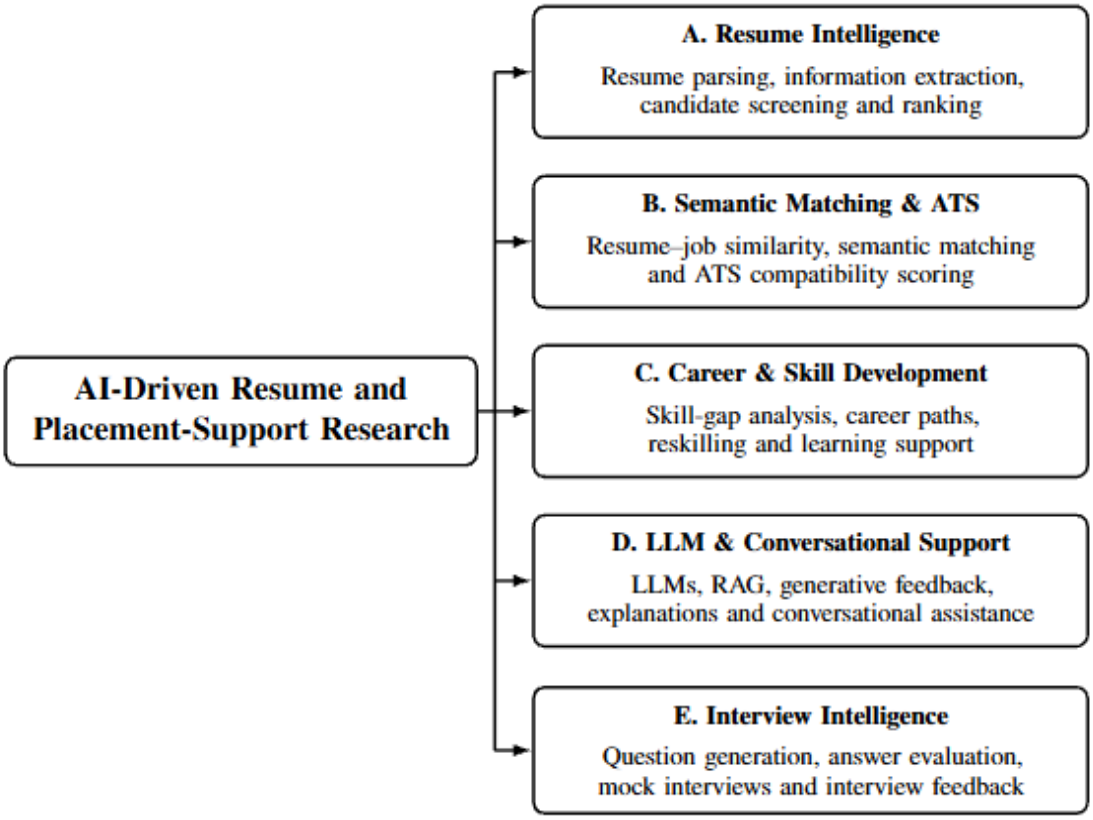


Fig. 1 Taxonomy of the reviewed studies based on their primary research focus

Table I presents the five major research themes identified in the reviewed literature, summarizing their primary purposes and the representative papers associated with each theme.

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TABLE I ANALYTICAL THEMES AND REPRESENTATION PAPERS

Theme	Primary purpose	Representative papers
A. Resume intelligence	Resume parsing, information extraction, skill identification, screening and candidate ranking.	1, 2, 3, 5, 6, 7, 8, 10, 11,12, 17, 18, 20
B. Semantic matching &ATS	Compare candidate profiles with job requirements using similarity, semantic representations, ranking, and ATS-oriented scoring.	2, 4, 5, 9, 10, 11, 12, 15,16, 17
C. Career & skill development	Identify skill gaps, recommend career directions, and support reskilling or learning.	5, 9, 13, 14, 15, 16, 17
D. LLM & conversational support	Use generative models, RAG, or LLMs for contextual analysis, feedback, explanations, and assistance.	4, 8, 18, 19
E. Interview intelligence	Generate interview questions, evaluate candidate responses, and provide mock-interview feedback.	18, 19

IV. LITERATURE REVIEW BY RESEARCH THEME

A. Resume Parsing and Information Extraction

Resume parsing is a foundational capability because subsequent screening, matching, recommendation, and skill-gap analysis depend on the quality of the extracted candidate profile. Ganesan et al. [1] apply preprocessing followed by BERT for skill extraction and job-role classification, reporting 97% accuracy. Kalpund et al. [3] implement resume extraction in Python/Django and report 88% accuracy, 80% consistency, and an average processing time of 2.1 seconds. Suresh et al. [5] use an attention-based neural network to emphasize relevant resume information and extract experiences, skills, and certifications, while Gautam et al. [20] combine NER, preprocessing and format standardization with BERT/RoBERTa fine-tuning to handle varied resume formats. Earlier approaches illustrate the limitations of surface-level processing. Pant et al. [6] use Tika Parser, keyword matching, regex, and character positioning and report 33.59% correct skill extraction on the reported test set. Panda et al. [7] evaluate Bag-of-Words, TF-IDF and Word2Vec representations with multiple classifiers across 960 resumes and 25 categories, reporting 99.5% for Bag-of-Words with Naive Bayes and 100% for TF-IDF with SVM under their evaluation setting. Deshmukh and Bendre [2] similarly use TF-IDF, KNN and cosine similarity for resume analysis and matching. These results demonstrate that conventional methods can be effective for constrained datasets and classification tasks, but their dependence on lexical or engineered representations can limit contextual interpretation. The later studies extend extraction toward semantic and structured representations. Alderham and Jaha [10] analyse 228 resumes in Microsoft Word Document (DOC), Microsoft Word Open XML Document (DOCX), and Portable Document Format (PDF) formats using semantic/comparative attributes and Ranking SVM, while Anghel et al. [11] combine NLP/BERT extraction with eXtreme Gradient Boosting (XGBoost) for curriculum vitae (CV)–job classification. Lo et al. [8] further separate resume extraction from subsequent evaluation, summarization, and scoring through a multi-agent RAG-LLM architecture. Overall, the literature supports increasingly contextual resume intelligence, while also showing that extraction robustness, format variation, and downstream integration remain important concerns.

B. Screening, Ranking, Semantic Matching and ATS

A second major research stream compares candidate profiles with job requirements and ranks candidates or jobs according to suitability. Deshmukh and Bendre [2] use TF-IDF, KNN, and cosine similarity for resume analysis and job matching. Chandak et al. [17] combine PDFMiner and spaCy-based extraction with TF-IDF and cosine similarity to produce content-based job recommendations, while Singh et al. [16] use Python/regex parsing, TF-IDF, machine-learning classification, Logistic Regression, and the LinkedIn Application Programming Interface (API) to connect resume information with job openings. Their comparison reports 99.48% accuracy for Decision Tree, Logistic Regression, AdaBoost, and SVM, with Logistic Regression offering high performance with low training time.Semantic approaches attempt to overcome the limitations of direct keyword overlap. Pagar [4] combines NLP and semantic matching with Large Language Model Meta AI (LLaMA) 3.3-70B and ATS scoring for role-based resume optimization, reporting an improvement in ATS score from 46% to 61%. Prasanna et al. [9] integrate DistilBERT NER, a transformer-based

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ATS classifier, cosine similarity, and feedback-based retraining, reporting 91.5% ATS accuracy, 91.4% F1, Precision@5 of 78%, and normalized Discounted Cumulative Gain (nDCG)@10 of 0.86. Alderham and Jaha [10] use semantic and comparative attributes with Ranking SVM, reporting up to 92% accuracy for candidate comparison and ranking. Tripathi et al. [12] use TF-IDF and BERT-based semantic matching with weighted ranking and evaluate the system using precision, recall, and F1. The reviewed studies therefore show a progression from lexical similarity toward contextual representations and ATS-oriented evaluation. However, the reported metrics are not directly comparable because the studies use different datasets, labels, tasks, and evaluation protocols. Anghel et al. [11], for example, report 66% accuracy on real data despite using BERT-based extraction and XGBoost classification. This variation reinforces the need to evaluate integrated systems using task-specific metrics and realistic candidate/job data rather than relying on a single headline accuracy.

C. Job Recommendation, Skill Gaps and Learning

Job-oriented studies broaden the objective from identifying suitable jobs to understanding what a candidate should develop and which career directions may be appropriate. Ashrafi et al.[13] analyse resumes together with current job-market requirements, identify existing skills and gaps, recommend suitable career paths, and suggest personalized reskilling or upskilling programs. Qamhieh et al.[14] use academic, personal, and extracurricular information together with Myers–Briggs Type Indicator (MBTI) personality profiling and fuzzy logic to generate personalized engineering career recommendations.

Sribharathi et al.[15] provide a more directly integrated example by combining NER/TF-IDF-based resume processing, supervised machine learning for skill-gap analysis, BERT embeddings with cosine similarity for job matching, and decision-tree career paths. The study reports 91.8\% matching accuracy, 1.8 seconds processing time, and 89\% user satisfaction. These approaches demonstrate that candidate information can be extended beyond resume screening to career planning and competency development.

Despite this progress, learning support remains less represented than resume parsing and job matching in the reviewed set. The surveyed job-oriented systems generally focus on recommending roles, identifying gaps, or suggesting reskilling rather than examining how these functions interact with ATS evaluation, resume improvement, and interview preparation. This imbalance highlights the need for further research on how career development and placement-support functions can be studied in a more coherent and connected manner.

D. LLMs, Generative AI and Conversational Support

Large Language Models introduce more flexible forms of contextual analysis, generation, explanation, and interaction. Pagar.[4] uses Llama-3.3-70B through the Groq API for role-based resume enhancement and ATS comparison. Lo et al.[8] propose a multi-agent RAG-LLM framework that separates resume extraction, evaluation, summarization, and score formatting. Their evaluation on anonymized resumes compares AI-generated scores with HR ratings and reports a Pearson correlation of 0.84 and a mean absolute error (MAE) of 0.90 for the reported DeepSeek-V3 setting. The study also emphasizes the continuing importance of changing job requirements, multimodal assessment, bias, and privacy.

The LLM literature also demonstrates the feasibility of generative assistance for interview preparation. Q\&AI.[18] combines resume extraction with BERT/RoBERTa/ChatGPT-based question generation and audio/video interview analysis, Brintha et al.[19] propose an AI-powered interview-preparation architecture using Generative Pre-trained Transformer 4 (GPT-4), Claude, LLaMA, and Mistral for role-specific question generation, NLP-based answer evaluation, competency mapping, dynamic questioning, and personalized feedback. These studies indicate that LLMs can support context-sensitive candidate interaction, but the reviewed systems generally use the candidate profile for a particular task rather than maintaining a unified placement profile across all preparation stages.

E. AI-Powered Interview Preparation

Interview preparation represents a distinct stage of placement in which the candidate must demonstrate technical knowledge, communication, confidence, and role-specific competencies. Q\&AI.[18] uses resume information to generate interview questions and supports audio/video interaction, including sentiment and emotion analysis, followed by a scorecard. Brintha et al [19] focus on LLM-based interview preparation, generating technical and behavioral questions and applying NLP-based answer evaluation and competency mapping to provide personalized feedback.

The interview studies demonstrate that AI can reduce the effort required to generate role-specific practice questions and provide structured feedback. However, their primary contribution remains interview practice rather than end-to-end placement preparation. In particular, the reviewed interview systems are not generally connected to ATS compatibility, resume improvement, skill-gap analysis, learning guidance, or career recommendation through a continuously updated candidate profile. This separation supports the need for a workflow in which interview preparation can be informed by the candidate's target role, resume evidence, and previously identified competency gaps.

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V. COMPARATIVE ANALYSIS OF THE STUDIES

Table II provides a consistent synthesis of all studies using method, reported finding, and key gap. The reported metrics are reproduced as study-level findings and should not be interpreted as directly comparable benchmark results.

TABLE II COMPARATIVE SYNTHESIS OF STUDIES

No.	Study	Method / reported findings	Key gap
1.	Smart Recruitment:BERT-Powered Resume Parsing for Accurate Skill Identification [1]	Resume preprocessing followed by BERT-based skill extraction and job-role classification; 97% accuracy.	Focuses on skill extraction and job-role classification; does no address ATS evaluation, skill-gap development, learning guidance, interview preparation, or conversational assistance.
2 .	Analysis and Ranking Resume using Machine Learning Algorithms and NLP [2]	NLP, TF-IDF, KNN and cosine similarity for resume analysis and job matching; 85% parsing accuracy.	Similarity-based processing may miss deeper semantic meaning; broader contextual relationships and downstream candidate support functions are outside its scope.
3.	AI-Powered Resume Parsing using Django: A Smart Recruitment Solution [3]	Python/Django extraction of skills, education and experience with matching and ranking; 88% accuracy, 80% consistency, 2.1 s processing	Sensitive to resume layouts and structured data; evaluation is primarily focused on parsing and screening.
4.	CVision: An AI-Powered System for Smart Resume Enhancement and Job Role Alignment [4]	NLP/semantic matching, GroqAPI with Llama-3.3-70B, ATS scoring and role-based resume optimization; ATS improved from 46% to 61%.	Concentrates on resume enhancement, ATS scoring, and role alignment rather than broader career-development and interview functions.
5.	Enhancing Resume Parsing and Job Recommendation Systems with Attention-Based Neural Networks and Collaborative Filtering [5]	Attention-based neural networks extract skills, experience and certifications; collaborative filtering uses preferences and history for recommendations; 94.1% validation accuracy and 0.045 validation loss.	Focus remains on parsing and job recommendation, with limited coverage of ATS evaluation, skill development, and interview support.
6.	Automatic Software Engineering Position Resume Screening using Natural Language Processing, Word Matching, Character Positioning, and Regex [6]	Tika Parser, NLP, keyword matching, regex and character positioning; 33.59% correct skill extraction on the reported test set.	Strong dependence on keywords and format-sensitive extraction, which limits contextual interpretation.
7.	Optimizing Resume Screening with Machine Learning: An NLP Approach [7]	960 resumes across 25 categories; Bag-of-Words, TF-IDF, Word2Vec and six classifiers; reported 99.5% for BoW + Naive Bayes and 100% for TF-IDF+SVM.	Results are task- and dataset-specific; broader contextual modelling and external validation remain relevant.
8.	AI Hiring with LLMs: A Context-Aware and Explainable Multi-Agent Framework for Resume Screening [8]	Multi-agent RAG-LLM with extraction, evaluation, summarization and scoring agents; DeepSeek-V3 reported 0.84 Pearson correlation and 0.90 MAE in the reported setting.	Changing job requirements, multimodal assessment, bias, privacy, explainability, and broader real-world validation remain challenges.
9.	Resume AI Suite: An Integrated NLP Framework for ATS-Optimized Scoring and Semantic Job Recommenda tion [9]	DistilBERT NER, transformer based ATS classifier, cosine similarity, and feedback-based retraining; 91.5% ATS accuracy,91.4% F1, Precision@5 78%, nDCG@10 0.86	Does not extend its ATS and recommendation framework to skill-gap analysis, structured interview preparation, or conversational support

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10.	Comparative Semantic Resume Analysis for Improving Candidate Career Matching [10]	228 DOC/DOCX/PDF resumes, NLP, semantic/comparative attributes, and Ranking SVM; upto 92% accuracy.	Mainly addresses semantic resume comparison and ranking; broader downstream candidate-support functions are outside its scope.
11.	Rule-Based AI for Resume–Job Matching in Recruitment Systems[11]	NLP/BERT extraction, XG-Boost CV–job classification ,skills/education/ Experience features, and deployment using Docker/ Kubernetes; 66%accuracy on real data.	Primarily addresses recruitment-side matching; candidate development and learning support are outside its main scope.
12.	NLP-Powered Resume Screening and Ranking System [12]	NLP feature extraction, TF-IDF and BERT semantic matching, weighted ranking, and precision/recall/F1 evaluation.	BERT-based matching provides stronger contextual representation than purely lexical comparison, while TF-IDF remains limited by context and synonyms; broader candidate-support functions are outside the study scope.
13.	Efficient Resume Based Re-Education for Career Recommendation in Rapidly Evolving Job Markets [13]	Resume and job-market analysis, skill-gap identification, career recommendation, and personalized reskilling/upskilling.	Focuses on career recommenda-tion and reskilling rather than integrated resume evaluation, ATS scoring, and interview support.
14.	PCRS: Personalized Career-Path Recommender System for Engineering Students[14]	Academic, personal and extracurricular information, MBTI personality profiling, and fuzzy logic for engineering career recommendation.	Relies on a broader personal and academic profile and does not directly evaluate resume-job fit or interview performance.
15.	Scopira: An AI-Driven Career Guidance System Using Resume Parsing, Skill Gap Analysis, and Intelligent Job Matching [15]	NER/TF-IDF parsing, supervised ML for skill gaps, BERT embeddings with cosine similarity, and decision-tree career paths; 91.8% matching accuracy, 1.8 s processing, 89% user satisfaction.	Does not cover ATS-oriented scoring, interview preparation, or conversational assistance within the same study.
16.	CAREER COMPASS:AI-Based Resume Parser and Automated Job Recommendation System [16]	Python/regex parsing, TF-IDF, ML classification and Logistic Regression, with LinkedIn API for job openings; Decision Tree, Logistic Regression, AdaBoost and SVM achieved 99.48% in the reported comparison.	Diverse-format, multilingual, and bias-related evaluation remains limited; the primary emphasis is job recommendation.
17.	Resume Parser and Job Recommendation System using Machine Learning [17]	PDFMiner and spaCy parsing, regex/Matcher extraction, TF-IDF and cosine similarity, implemented as a Flask application for content-based recommendations.	Does not address skill-gap analysis, personalized learning, interview preparation, or conversational support.
18.	Q&AI: An AI Powered Mock Interview Bot for Enhancing the Performance of Aspiring Professionals [18]	Resume extraction with BERT/RoBERTa/ChatGPT question generation, audio/video interview interaction, sentiment/emotion analysis, and scorecard generation.	Primarily interview-focused; interactions with resume scoring, career recommendation, and learning support are outside its main scope.
19.	Design and Implementation of an AI-Powered Interview Preparation Platform using Advanced LLM Architectures [19]	GPT-4, Claude, LLaMA and Mistral for role-specific question generation, NLP-based answer evaluation, competency mapping, dynamic questioning, and personalized feedback.	Interview-focused, with broader resume, ATS, skill-gap, and candidate-support integration outside its main evaluation scope.
20.	Automating Talent Acquisition Assisted by Resume Parsing System for Enhanced Job Matching [20]	NER and transformers with preprocessing, format standardization, and BERT/RoBERTa fine-tuning; designed to handle varied resume formats.	Focuses on parsing and job matching, with limited coverage of skill-gap analysis, ATS evaluation, and interview preparation.

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VI. FEATURE COVERAGE ACROSS THE REVIEWED STUDIES

Fig. 2 summarizes the thematic coding of the selected papers. The thematic counts are: resume parsing 18, ATS 2, semantic matching 16, skill-gap analysis 2, job recommendation 5, learning support 1, interview AI 2, and LLM/generative AI 4. These values represent thematic coding rather than a statistical meta-analysis; a feature is counted when it is clearly represented in the surveyed scope of a study. For thematic coding, "job recommendation" includes systems that recommend suitable job roles or job opportunities based on candidate information, while "semantic matching" includes approaches that compare candidate information with job or role requirements using similarity measures, contextual representations, or ranking methods.

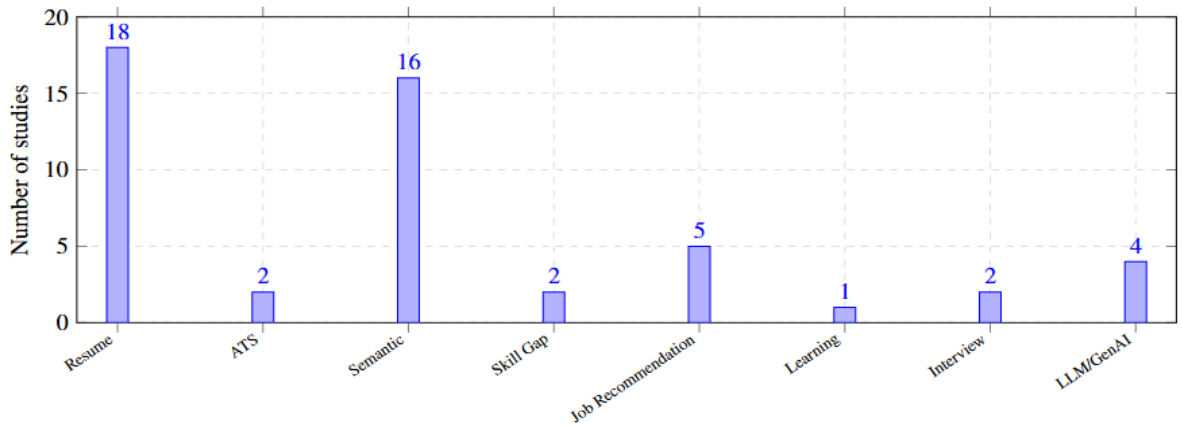


Fig. 2 Feature coverage across the reviewed studies.

Table III presents the feature coverage matrix of the 20 reviewed studies, indicating which key features, such as resume parsing, ATS scoring, semantic matching, skill-gap analysis, job recommendation, learning support, interview preparation, and LLM-based assistance, are addressed by each study.

TABLE III. FEATURE COVERAGE MATRIX

No.	Resume	ATS	Semantic	Skill Gap	Job Recommendation	Learning	Interview	LLM
1	✓	–	✓	–	–	–	–	–
2	✓	–	✓	–	–	–	–	–
3	✓	–	✓	–	–	–	–	–
4	✓	✓	✓	–	–	–	–	✓
5	✓	–	✓	–	✓	–	–	–
6	✓	–	–	–	–	–	–	–
7	✓	–	✓	–	–	–	–	–
8	✓	–	✓	–	–	–	–	✓
9	✓	✓	✓	–	✓	–	–	–
10	✓	–	✓	–	–	–	–	–
11	✓	–	✓	–	–	–	–	–
12	✓	–	✓	–	–	–	–	–
13	✓	–	✓	✓	–	✓	–	–
14	–	–	–	–	–	–	–	–
15	✓	–	✓	✓	✓	–	–	–
16	✓	–	✓	–	✓	–	–	–
17	✓	–	✓	–	✓	–	–	–
18	✓	–	–	–	–	–	✓	✓
19	–	–	–	–	–	–	✓	✓
20	✓	–	✓	–	–	–	–	–

It shows a progression from lexical and rule-based processing toward contextual representation and generative architectures. Earlier or baseline studies rely on regex, keyword matching, TF-IDF, Bag-of-Words, cosine similarity, conventional classifiers, and fuzzy logic. Transformer-based approaches introduce contextual representations through BERT, RoBERTa, DistilBERT, and related architectures, while attention-based neural networks improve the ability to emphasize relevant resume information. The most recent studies extend these capabilities with Llama-based generation, RAG-LLM, multi-agent architectures, and LLM-based interview assistance. These categories overlap because a study

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can combine multiple technology families. The trend should therefore be interpreted as a qualitative evolution rather than a mutually exclusive count of papers. The main shift is from surface-level matching toward systems that can represent context, generate explanations or feedback, and adapt outputs to a candidate or role.

Fig. 3 shows that contextual and neural approaches are the most represented in the reviewed studies, followed by traditional NLP/ML and LLM-based approaches, while Table IV summarizes the key techniques, strengths, and limitations associated with each technology family.

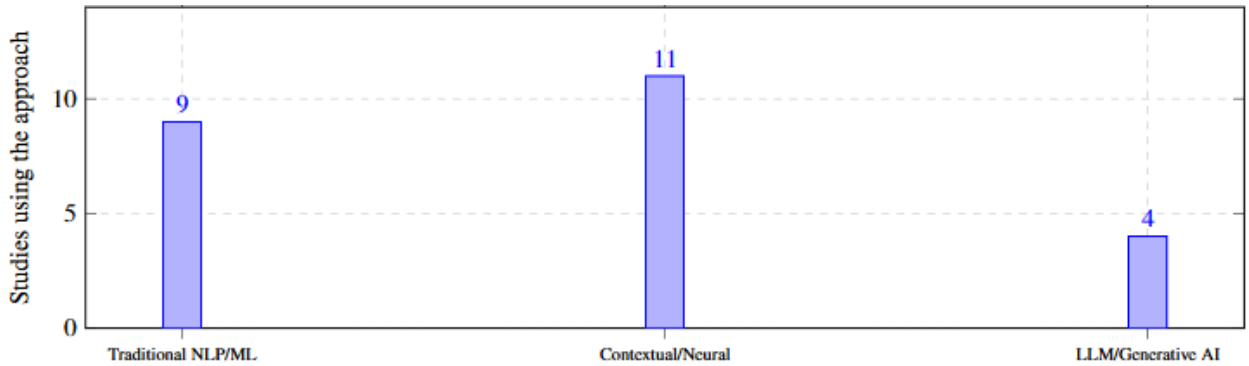


Fig. 3 Technology families observed in the reviewed literature; categories may overlap because individual studies may use more than one technology family.

Table IV TECHNOLOGY EVOLUTION AND OBSERVED LIMITATION

Stage	Typical techniques	Strength	Observed limitation
Traditional NLP / ML	Regex, keyword matching, TF-IDF, Bag-of-Words, KNN, SVM, Logistic Regression	Efficient, comparatively simple, and useful as baselines	Context/synonym limitations; sensitivity to unstructured text.
Deep learning / Transformers Generative / LLM-based	Word2Vec,BERT,RoBERTa, DistilBERT,attention networks Llama, ChatGPT, GPT-4, Claude, Mistral, RAG-LLM,multi-agent systems	Better contextual and semantic representation. Flexible generation, explanation, and personalized interaction.	Higher complexity; dataset and evaluation dependence. Bias, privacy, changing requirements, and reliability concerns.

VIII. PUBLICATION TREND IN THE PAPER SET

The selected literature is concentrated in recent years, with one paper from 2020, two from 2022, one from 2023, five from 2024, ten from 2025, and one from 2026. This distribution reflects the recent acceleration of research activity around AI-assisted recruitment, semantic matching, LLMs, and placement-support applications within the selected literature set.

Fig. 4 shows that the selected literature is concentrated in 2024 and 2025, with 10 studies published in 2025 and 5 in 2024, indicating a recent increase in research on AI-assisted recruitment, semantic matching, and placement-support systems within the reviewed paper set.

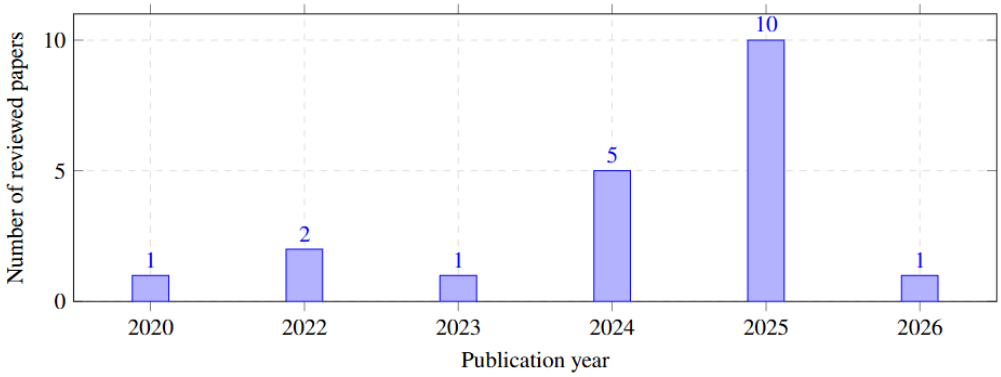


Fig. 4 Publication-year distribution of the selected studies

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X. CROSS-STUDY FINDINGS

A. Resume intelligence is the most established capability

Resume parsing, skill extraction, screening, and candidate ranking appear across most of the reviewed studies. The literature demonstrates a clear movement from regex and keyword-based extraction toward BERT, attention-based neural networks, and structured or semantic representations.

B. Semantic matching is replacing purely lexical comparison

TF-IDF and cosine similarity remain useful baselines, but several studies increasingly incorporate BERT-family models, semantic attributes, and LLMs to capture contextual relationships between resumes and job requirements. This transition improves the ability to handle synonyms and contextual meaning, although performance remains dependent on the dataset and evaluation task.

C. ATS capability is comparatively limited

Only a small subset of the reviewed studies explicitly addresses ATS-oriented scoring. Pagar [4] and Prasanna et al. [9] demonstrate that ATS evaluation can be integrated with resume enhancement and semantic recommendation, but ATS functionality is not commonly combined with career development and interview preparation.

D. Career and skill development remain fragmented

Studies [13], [14], and [15] show that AI can identify skill gaps and recommend career directions or reskilling pathways. However, learning support is rarely connected to the same workflow as resume optimization, ATS analysis, job matching, and interview practice.

E. Interview intelligence forms a separate stream

Studies [18] and [19] demonstrate resume-aware question generation, multimodal interaction, answer evaluation, competency mapping, and personalized feedback. Their primary focus remains interview practice rather than continuous placement preparation across multiple candidate-support functions.

F. LLM-based systems increase flexibility but introduce new concerns

LLM and RAG-based approaches enable contextual feedback, explanation, generation, and multi-step processing. At the same time, the reviewed work highlights privacy, bias, changing job requirements, multimodal assessment, and reliability as important considerations for deployment.

G. Reported performance values are not directly comparable

The studies differ in datasets, task definitions, labels, baselines, and evaluation metrics. Consequently, high accuracy in one study should not be interpreted as evidence that its approach universally outperforms another study. The more meaningful cross-study finding is the progression of capabilities and the distribution of functions across systems.

X. RESEARCH GAP SYNTHESIS

The reviewed studies demonstrate substantial progress across a range of AI-supported placement activities, including resume parsing, candidate screening, semantic job matching, ATS-oriented scoring, job recommendation, skill-gap analysis, learning support, conversational assistance, and interview preparation. Studies such as Ganesan et al. [1], Prasanna et al. [9], Sribharathi et al. [15], and Brintha et al. [19] address different aspects of these activities. Rather than indicating a lack of effective techniques, the literature shows that these capabilities have been explored through different approaches, datasets, and evaluation objectives, with each study addressing a particular aspect of the placement process. The central research gap can therefore be described as an integration and evaluation gap. Within the reviewed paper set, most studies focus on a single task or a limited combination of tasks, while relatively few investigate how candidate information can be maintained and used consistently across multiple stages, such as resume analysis, job matching, skill development, job recommendation, and interview preparation. Although Sribharathi et al. [15] combine resume parsing, skill-gap analysis, and job matching, interview-focused studies such as Q&AI [18] and Brintha et al. [19] primarily address interview preparation. Consequently, there is limited evidence on the effectiveness of such processes when considered as a connected, end-to-end workflow.

This functional fragmentation is accompanied by several methodological gaps. Direct comparison of reported performance remains difficult because the reviewed studies use different datasets, task definitions, evaluation criteria, and experimental settings. Resume parsing studies differ in the resume formats they support and the entities they extract, while matching studies employ different similarity measures and ranking strategies. For example, Kalpund et al. [3] focus

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on automated resume extraction, whereas Prasanna et al. [9] incorporate ATS scoring and semantic job recommendation. Similarly, job recommendation systems often rely on domain-specific candidate profiles, and interview-support systems use varying criteria to assess generated questions, candidate responses, and feedback. These differences make it difficult to determine whether one approach consistently outperforms another across different applications.

The literature also points to several unresolved challenges, including explainability, fairness, privacy, changing job-market requirements, the reliability of AI-generated content, and the handling of multilingual and multimodal inputs. Lo et al. [8] highlight concerns related to explainability, bias, privacy, and changing job requirements in LLM-based resume screening. In AI-assisted interview assessment, the validity and consistency of automated evaluation remain important areas for further investigation [18], [19]. Addressing these challenges is essential for moving beyond isolated task-specific solutions toward AI-supported placement systems that are more integrated, reliable, generalizable, and responsibly evaluated.

XI. RESEARCH IMPLICATIONS

The collective evidence suggests that future research should move beyond isolated task performance while retaining rigorous module-level evaluation. Resume extraction, semantic matching, ATS analysis, job recommendation, skill-gap analysis, learning support, and interview intelligence should be studied not only as individual functions but also in terms of how their outputs can inform one another. Existing work on integrated resume analysis and job matching [15] and LLM-based interview preparation [19] illustrates the potential for connecting different placement-support activities.

An important implication is the need for a consistent representation of candidate information. Resume-derived skills, education, experience, certifications, target roles, and identified gaps could serve as shared evidence across multiple research tasks. Such continuity would enable systematic investigation of whether information extracted at one stage improves downstream matching recommendation, learning, or interview performance.

The literature also suggests that integration should not replace task-specific validation. Each function requires appropriate metrics datasets, and human or domain-expert assessment. Differences in evaluation methods across resume screening and ATS-oriented systems [7], [9] highlight the importance of evaluating each component according to its intended purpose. A broader research agenda should therefore combine component-level performance with end-to-end measures of relevance, consistency, usability, fairness, privacy, and reliability.

Resume Understanding → Job Matching / ATS → Skill-Gap Analysis → Career and Learning Support → Interview Intelligence

The sequence above represents a research integration opportunity derived from the literature rather than an implemented system. It illustrates how the reviewed research areas could be investigated as connected stages while preserving separate validation criteria for each task.

XII. EVALUATION CONSIDERATIONS FROM THE LITERATURE

The reviewed studies demonstrate that no single metric is sufficient to evaluate the full range of AI-supported placement functions. Future comparative research should therefore use task-appropriate measures and clearly report dataset characteristics, annotation procedures, baselines, and experimental settings. Table V presents the evaluation considerations for the different research areas.

TABLE V LITERATURE GROUNDED EVALUATION CONSIDERATION

Research area	Suggested evaluation	Purpose
Resume/entity extraction	Precision, recall, F1, field-level error analysis, and format-wise evaluation.	Measures extraction quality across different resume structures and formats.
ATS / job matching	Accuracy/F1 for classification tasks; similarity and ranking metrics where appropriate.	Measures candidate–job alignment without conflating different task definitions.

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Job recommendation	Precision@K, nDCG, ranking quality, or expert relevance assessment.	Measures whether recommended jobs or roles are relevant to candidate profiles.
Skill-gap analysis	Agreement with expert-labelled gaps using precision, recall, F1, or structured expert review.	Tests whether identified deficiencies are meaningful and actionable.
Learning support	Expert relevance assessment, usefulness, satisfaction, and outcome-oriented measures.	Evaluates whether recommended learning actions address identified gaps.
Interview intelligence	Human rubric, question relevance, score correlation where appropriate, and user satisfaction.	Evaluates the quality and usefulness of generated questions and feedback.
Integrated workflows	Task completion time, consistency, usability, fairness, reliability, and end-to-end user evaluation.	Assesses whether combining functions provides measurable benefit without sacrificing trust or validity.

XIII. REVIEW LIMITATIONS

This review is limited to the selected literature and the methodological information available in the collected sources. It does not claim a fully reproducible PRISMA search process, exhaustive database coverage, or statistical meta-analysis. The reported accuracy, F1, ranking, processing-time, and satisfaction values are treated as study-level findings and should not be interpreted as directly comparable benchmark results, as the reviewed studies use different datasets, task definitions, and evaluation protocols [7], [9].

The thematic categories are not mutually exclusive. A study may contribute to more than one research area, and the feature-coverage counts therefore represent qualitative coding rather than independent statistical observations. In addition, publication years and bibliographic details should be checked against the final source versions before submission to a journal or conference.

XIV. FUTURE RESEARCH DIRECTIONS

To meaningfully advance this field, future research must first establish reproducible search, screening, and reporting protocols while expanding the scope of literature reviews to capture a broader range of relevant studies. Methodologically, the focus should shift toward developing format-flexible, multilingual, and multimodal resume-parsing techniques capable of generalizing across highly diverse candidate documents. Evaluating these innovations requires standard benchmarks that can test ATS, matching algorithms, and interview-support systems under uniform evaluation conditions [9].

Technical upgrades alone, however, are insufficient. Transparency must become a priority; researchers need to improve the explainability of semantic-matching scores so that both recruiters and applicants can scrutinize the logic behind automated decisions. This shift underscores a broader demand to rigorously audit conversational and screening systems for bias, privacy vulnerabilities, and ethical data handling. Furthermore, we must critically evaluate the factual reliability and controllability of LLM-generated career guidance, while questioning the validity of using sentiment or emotional signals in multimodal interview assessments to infer professional merit. Ultimately, systems should explicitly link identified skill gaps to evidence-based learning resources. Proving the real-world utility of these tools will require long-term, end-to-end studies to verify that integrated AI architectures deliver systemic improvements rather than merely optimizing isolated, task-level metrics.

XV. CONCLUSION

The reviewed studies cover five major areas of AI-supported resume analysis and placement preparation: resume intelligence; semantic matching and ATS; job recommendation and skill development; LLM and conversational support; and interview intelligence. The literature demonstrates a clear methodological progression from regular expressions (regex), keyword matching, TF-IDF, conventional classifiers, and similarity measures to transformer-based contextual representations, attention-based neural networks, recommendation methods, and Large Language Model (LLM) and Retrieval-Augmented Generation (RAG) architectures[8].



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The review shows that individual techniques can achieve strong task-specific results, but the evidence is heterogeneous and should be interpreted in the context of each study's dataset, task definition, and evaluation protocol. Resume parsing and semantic matching are the most extensively represented capabilities, while ATS evaluation, skill-gap analysis, learning support, conversational assistance, and interview intelligence appear in smaller and more specialized subsets.
The principal research opportunity is therefore not simply to improve one algorithm, but to investigate how multiple placement support functions can be connected and evaluated coherently. Future work should address functional integration together with explainability, fairness, privacy, reliability, multilingual and multimodal robustness, and standardized evaluation. Overall, the reviewed literature provides a consolidated foundation for understanding the current state and future direction of AI-driven resume analysis and personalized placement support.

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