INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 11, November 2026 | ISSN: 2456-4184 | IJNRD.ORG

# Career Recommendation Systems Powered by Artificial Intelligence: An Extensive Review on Resume Parsing, Job Matching, and Personalized Career Guidance

**[1]R Kirthana,[2]R Nitya Sree,[3]Shuban S,[4]Spoorthi S,[5]Dr. Kumaraswamy S**

[1]Student,[2]Student,[3]Student, [4]Student,[5]Head of Department
[1]Department of Information Science and Engineering,
[1]Global Academy of Technology, Bengaluru, India

***Abstract :*** Recent advances in artificial intelligence have reshaped the interaction between recruiters, career counselors and candidates. Resume parsing, semantic skill extraction, personalized job recommendation and candidate evaluation have emerged as central themes in this transformation. This paper surveys twenty studies on AI-driven career recommendation and recruitment, spanning machine learning, deep learning, natural language processing (NLP), named-entity recognition (NER), BERT-family transformer models, optical character recognition (OCR), generative AI, Random Forest, XGBoost and artificial neural networks. The reviewed literature reports progress in semantic resume parsing, applicant-tracking-system (ATS) enhancement, skill-gap identification, competency assessment, job-recommendation modelling and recruitment automation. Comparing these studies reveals a consistent gap: no reviewed system offers a single, end-to-end career-counseling pipeline that unifies semantic resume parsing, labor-market analysis, personalized recommendation, explainable reasoning and skill-gap analysis within one framework. To address this gap, the paper outlines ElevateHire, a proposed AI-powered career-recommendation and resume-analysis framework that integrates intelligent resume parsing, semantic job recommendation, skill-gap analysis, personalized learning recommendation and explainable career guidance. Overall, this review consolidates the current state of the art in AI-based career recommendation and recruitment and identifies concrete opportunities for developing more holistic, transparent and adaptive career-guidance systems.

***IndexTerms*** **- Artificial Intelligence, Career Recommendation Systems, Resume Analysis, Resume Screening, Machine Learning, Natural Language Processing, Semantic Matching, Skill-Gap Analysis, Personalized Learning, Explainable AI, Intelligent Recruitment.**

---

## I. INTRODUCTION

Artificial Intelligence (AI) has come to play a defining role in modern recruitment and career recommendation. A growing set of technologies now makes it possible to analyze an individual's resume, identify their skills, propose suitable job openings and screen candidates against defined criteria. As competition among recruitment platforms and professional networks intensifies, job seekers increasingly rely on intelligent virtual assistants to navigate the labor market, creating a clear need for AI-based recruitment and career-recommendation solutions.

Conventional recruitment relies heavily on keyword-based analysis performed through applicant tracking systems (ATS), an approach that is often imprecise because it cannot capture the semantic meaning behind a candidate's stated skills and experience. Modern Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), transformer architectures and Generative AI techniques have been developed to overcome this limitation. However, most existing systems are designed for a single task — such as resume analysis or job recommendation alone — leaving an open need for an integrated approach capable of delivering context-aware recommendations, processing multiple languages and incorporating up-to-date labor-market intelligence.

This paper reviews twenty academic studies on semantic resume analysis, personalized learning recommendation and automated recruitment, and uses the findings to motivate the need for an integrated, AI-driven approach to career recommendation.

### A. Motivation and Scope

The central challenge facing AI-based recruitment and career recommendation is capturing a candidate's competencies accurately and keeping recommendations aligned with a constantly changing labor market. Existing solutions typically automate a single stage of the process — resume screening, job matching or skill assessment — and are frequently built on relatively simple matching algorithms, which limits their flexibility, personalization and transparency. This paper examines this problem through a structured review of recent IEEE-indexed research on intelligent recruitment, semantic resume understanding, personalized recommendation systems and adaptive learning.

### B. Contributions of This Survey

This survey makes the following contributions: (1) a structured review of twenty IEEE-indexed research articles on AI-based career recommendation, intelligent hiring and resume analysis; (2) a comparison of the AI techniques employed across these works, including machine learning, deep learning, NLP, transformer-based architectures and generative AI; (3) identification of recurring research trends, namely semantic skill recommendation, explainable AI, personalized career recommendation and adaptive learning suggestion; (4) a consolidated view of the system-level barriers that limit current AI-based resume-analysis and recruitment systems, including the absence of unified multimodal architectures, limited personalization and explainability, restricted multilingual support, privacy concerns and the inability to incorporate real-time labor-market information; and (5) a proposed integrated AI-based framework — ElevateHire — for career recommendation and resume analysis that combines semantic resume understanding, intelligent job recommendation, skill-gap analysis, personalized learning suggestion and explainable recommendation.

## II. BACKGROUND

### A. Artificial Intelligence in Career Recommendation

AI has become an important enabler in the recruitment industry, offering new ways for computer systems to analyze job vacancies and recommend suitable positions. Most recruitment software in current use relies on NLP-driven applicant tracking systems (ATS) that apply rule-based filtering, sorting applications by matching keywords and skills against predefined criteria.

### B. Machine Learning for Intelligent Recruitment

Machine learning enables predictive, data-driven decision-making using historical employee and candidate data. Algorithms such as Decision Trees, Support Vector Machines, Random Forest, Artificial Neural Networks and XGBoost are used to filter, score and forecast candidate fit, while ensemble techniques further improve forecasting accuracy. Clustering algorithms are also used to group candidates by qualifications and skills, reducing the manual effort required for candidate filtering.

### C. Natural Language Processing for Resume Understanding

NLP techniques make it possible to extract meaningful information from unstructured text such as resumes and job descriptions. Tokenization, lemmatization, named entity recognition and semantic parsing help identify qualifications, technical skills, certifications and experience. Because NLP-based methods can recognize synonymous job-related terminology, they generally outperform traditional keyword-based matching in identifying candidate requirements.

### D. Large Language Models for Career Guidance

Recent advances in large language models (LLMs), including GPT- and LLaMA-based architectures, have enabled more intelligent career-recommendation systems capable of summarizing resumes, answering career-related questions and explaining recommendation outcomes in natural language. By supporting virtual, dialogue-based career consultation, these models are transforming conventional recommendation systems into interactive advisory tools.

### E. Labor Market Intelligence and Skill-Gap Analysis

The growth of online job portals and professional networks has produced large volumes of data describing available jobs, required skills and applied technologies. Analyzing this labor-market data allows recommendation systems to compare a candidate's current skill set with market requirements and provide targeted advice on the skills needed to secure specific opportunities.

### F. Knowledge-Based and Explainable Career Recommendation

Structured knowledge representations, such as occupational ontologies and knowledge graphs, capture relationships among skills, occupations, certifications and industries, improving the quality of recommendations. Standardized taxonomies such as ESCO and O*NET support the standardization of occupational data and strengthen the semantic reasoning capability of recruitment systems. Explainable Artificial Intelligence (XAI) is identified as an important complement to these techniques, since it makes the recommendation process understandable to end users.

## III. LITERATURE REVIEW

A systematic review of twenty studies reveals substantial progress in applying AI to career guidance and recruitment. Across these works, existing solutions tend to target a specific task — such as resume assessment, career advice, or job matching — but none of the reviewed studies presents a holistic, personalized system that supports a user across the entire career-development journey.

### A. AI-Based Career Path and Pathway Recommendation

Recent work has explored AI for personalized counseling and career-path recommendation, moving from machine-learning-based career prediction and psychometric evaluation toward interactive labor-market access and hybrid techniques that combine structured user features with semantic resume analysis [1], [2], [6]. AI-powered career-support systems have also been developed to assist with institution assessment and university-prospectus exploration [7]. However, these solutions remain fragmented — no reviewed system offers an integrated platform spanning career exploration, skill-gap assessment, personalized learning, internships, job opportunities and further education, motivating the need for a more holistic career-development framework.

**B. Skill Gap Analysis and Personalized Learning**

Several studies focus on detecting missing skills and generating personalized learning recommendations to support career development. AI-based skill-gap-analysis methods identify missing competencies and recommend improvements based on user profiles, resumes and job-market requirements [5], [7]. A separate line of work applies deep learning to model learner behaviour, preferences and patterns in order to recommend personalized learning paths and sequences [15]. Both approaches show that combining learner profiles with skill requirements can produce effective up-skilling recommendations; however, few studies connect skill-gap identification directly to project, internship, job or career planning.

**C. Resume Generation, Analysis and Optimization**

Some systems generate resumes automatically from structured user input using predefined templates [10], [17], while others apply NLP and machine learning to analyze resumes for skill and formatting gaps, optimize keyword usage and re-rank resumes against job descriptions and domain standards [15]. Related frameworks apply AI to generate and filter resumes for campus-recruitment scenarios, improving both preparation and evaluation [16]. Across these studies, AI is used predominantly to support resume creation rather than broader career development.

**D. Intelligent Job Recommendation and Job Matching**

Intelligent job-recommendation systems use candidate profile, skill, resume and job-description data to recommend suitable openings. Methodologies range from rule-based skill matching to semantic similarity, collaborative filtering, resume analysis and automated job-data crawling [9], [10]. These systems are effective at automating job discovery and alerting candidates to relevant opportunities, demonstrating the strength of AI and ML for job matching; however, most focus solely on the final matching stage rather than the earlier stages of career-path selection, skill-gap identification, personalized learning, resume enhancement and internship discovery that a comprehensive system would also need to address.

**E. AI-Based Resume Screening and Recruitment**

Automation has also been applied to resume ranking, candidate ranking and recruitment workflows to reduce manual screening effort. NLP-based resume-ranking tools rank candidate profiles against job descriptions [8], [12], while multi-modal transformer-based approaches incorporate speech processing and sentiment analysis to rank candidates using multiple data modalities [3]. These studies demonstrate the potential for more efficient recruitment but remain oriented toward screening and matching rather than broader career guidance.

**F. Integrated Student Support and Placement Preparation**

A further body of work proposes centralized platforms that support students with academic, professional and placement-related activities. AI-embedded educational support platforms with chat assistance help students access academic data repositories efficiently [4], while placement-oriented platforms offer smart placement-preparation capabilities for recruitment drives run by employers [14], [17]. Although combining multiple student services in this way reduces fragmentation, existing platforms generally emphasize either academic assistance or placement preparation, without connecting career aspirations to skill gaps, personalized learning, resume creation, internships, jobs and higher-education opportunities in a single system.

**G. Summary of Literature Review Findings**

Collectively, the reviewed papers demonstrate substantial progress in applying AI, machine learning, NLP, deep learning and recommendation techniques to career guidance, career-path recommendation, skill-gap analysis, adaptive learning, resume generation and optimization, job matching, recruitment, academic assistance and placement preparation. Most of these innovations, however, remain stand-alone solutions rather than components of an integrated career-development life cycle. None of the reviewed studies offers a complete solution spanning personalized career discovery, skill-gap identification, adaptive learning, project work, internships, resume generation, job opportunities and higher-education or scholarship guidance within a single, unified platform.

## IV. COMPARATIVE ANALYSIS

Table I consolidates the twenty reviewed studies with respect to their methodological approach, technologies employed, dataset (where reported), principal findings and the research gap identified in each. Fields not explicitly reported in a given study are marked accordingly, in line with the review's evidence-based scope.

*Table 1:COMPARATIVE SUMMARY OF REVIEWED STUDIES ON AI-BASED CAREER RECOMMENDATION AND RESUME ANALYSIS SYSTEMS*

| Ref. | Paper / System | Year | Method / Approach | Technologies | Dataset | Key Findings | Research Gap / Limitations |
|---|---|---|---|---|---|---|---|
| [1] | AI-Powered Career Guidance (RIASEC Model) | 2026 | Decision Tree, SVM, XGBoost classifiers on psychometric data | ML (Decision Tree, SVM, XGBoost) | Cross-sectional self-reported dataset | Four model variants compared for predicting psychometric elements relevant to career fit | Older cross-sectional dataset; relies on self-reported jobs; considers only RIASEC interests |
| [2] | Sankalp: AI-Powered Career | 2025 | Semantic reasoning, adaptive | SBERT, VADER, Naukri job API | Job postings retrieved via Naukri API | 77.5% top-1 and 90.5% top-3 recommendation | Needs expert/external validation and |

| Ref. | Paper / System | Year | Method / Approach | Technologies | Dataset | Key Findings | Research Gap / Limitations |
|---|---|---|---|---|---|---|---|
| | Guidance System | | learning and emotional analysis combined for guidance | | | hit rate; 4.71 user satisfaction score | advanced generative models for deeper personalization |
| [3] | Deep Learning-Driven Labor Education and Skill Assessment | 2025 | LLM fine-tuning for resume screening and grading | LLaMA2-13B, FLAN-T5, GPT-NeoX (SOTA LLMs) | Not explicitly reported | Fine-tuned LLaMA2-13B improved resume evaluation by 27% over zero-shot models | Evaluates only from a recruiter/screening perspective; struggles with long-context resumes; no integrated grading-summarization pipeline |
| [4] | Extraction of Metadata for Recommendation Using Keyword Mapping | 2024 | Object detection and speech-to-text used to build contextual metadata for recommendation | YOLO, Google Speech-to-Text, TextRank, hybrid recommendation | MovieLens dataset | Context-rich metadata improved recommendation quality and mitigated cold-start/long-tail issues | Keyword mapping relies on genre categories rather than titles; limited to media-domain recommendation |
| [5] | Big Data Software Engineering: Knowledge Domains via LDA | 2019 | Probabilistic topic modelling of job/skill data | Latent Dirichlet Allocation (LDA) | Job advertisement text corpus | Identified latent skill sets mapped to competency domains in big-data software engineering | Focuses on competency identification only, not automated content analysis of job ads |
| [6] | A Seamless ChatGPT Knowledge Plug-in for the Labour Market | 2024 | Conversational plug-in linking LLM with structured occupational knowledge bases | ChatGPT plug-in, O*NET, ESCO, NLP retrieval | O*NET / ESCO occupational databases | Enables users to explore skills, roles and learning opportunities via natural-language queries | Limited personalization, skill-gap analysis and career-pathway depth |
| [7] | Real-Time AI-Based Skill Gap Analysis and Adaptive Career Guidance | 2025 | Generative AI platform for real-time skill-gap analysis and resume tailoring | Generative AI, NLP, competency testing, InsightFace/Buffalo-L | Not explicitly reported | Integrated resume generation, skill-gap analysis and competency assessment improve employability | Focused mainly on employability; projects, higher education and scholarships not covered |
| [8] | SATYA: AI-Driven Talent Yield Analyzer | 2024 | Resume screening and candidate evaluation with claim validation | spaCy, BERT, TF-IDF, RoBERTa, LanguageTool | Recruiter resume dataset (not detailed) | 91.4% accuracy in resume-quality prediction; validates reliability and skill authenticity | Designed for recruiter-side screening only; no personalized skill-gap analysis or learning path |
| [9] | JobLinker: Automated Recruitment through Verified Intelligence | 2026 | Integrated job-seeker/recruiter platform with AI-driven matching | MERN stack, NLP, ML, AI-based recommendation | Not explicitly reported | Improves job discovery and recruiter-candidate interaction through AI recommendation and tracking | Focused on job search/recruitment only; no career-pathway, skill-gap or learning support |
| [10] | Career Bridge: MERN-Based Recruitment Platform | 2025 | Integrated recruitment platform emphasizing usability and | MERN stack, ML-based job matching, AI resume screening, JWT | Not explicitly reported | Delivers personalized job recommendations, resume upload, dashboards and | Does not integrate skill-gap analysis, personalized learning, internships or |

| Ref. | Paper / System | Year | Method / Approach | Technologies | Dataset | Key Findings | Research Gap / Limitations |
|---|---|---|---|---|---|---|---|
| | | | reliability | authentication | | real-time recruiter communication | higher-education pathways |
| [11] | ResumeInsight: Semantic Resume-Job Matching and Skill-Gap Analysis | 2025 | Semantic matching and skill-gap detection with resume parsing | PyMuPDF, spaCy, Levenshtein distance, Random Forest, XGBoost, ANN | Not explicitly reported | Achieved ~75% accuracy in performance prediction; Random Forest performed best | Focused on resume-job matching; does not address holistic career development |
| [12] | Resume Ranker for Freshers using NLP | 2025 | Automatic resume ranking against job descriptions | spaCy, TF-IDF, cosine similarity, Logistic Regression, Random Forest | Fresher resume dataset (not detailed) | 90.2% accuracy, 88.6% precision, 89.2% recall, 89.0% F1-score | Recruiter-side ranking only; provides no skill-improvement guidance |
| [13] | Hybrid AI Framework: SBERT + TabTransformer for Career Path Recommendation | 2025 | Hybrid recommendation combining unstructured resume text with structured academic data | SBERT, TF-IDF, TabTransformer, LLM-backed chatbot layer | Not explicitly reported | 73% accuracy using SBERT+cosine on raw summaries; 95.9% combining TF-IDF with deep learning model | Focused on career suggestion/skill identification; no user dashboard |
| [14] | Blitz: Student Life Goal Assistant Application | 2025 | Mobile assistant offering talent hunt, higher-study and scholarship information | Flutter, Google Firebase | 448 user reviews (app-store feedback) | 56% of users rated the app highly satisfactory | Lacks resume analysis, skill-gap identification and recommendation |
| [15] | Deep Learning-Based Learning Path Recommendation | 2025 | Personalized learning-path generation from behavioural patterns | Bi-LSTM, PyTorch | Learner behavioural/preference dataset (not detailed) | 89.4% precision and 85.7% recall; adapts dynamically to learning behaviour | Focused on personalized education only; no integrated career/job recommendation |
| [16] | CareerCraft: Crafting Your Future, One Code at a Time | 2025 | AI-driven platform for resume upload, simulated AI interviews and study-path generation | NLP, BERT-based APIs | Not explicitly reported | 90% effectiveness in skill extraction/CV analysis; 85% interviewer feedback; 70% roadmap generation | Focused on placement preparation and learning; further personalization left for future work |
| [17] | Smart Campus Placement System | 2025 | Full-stack web application for resume generation and candidate filtering | GPT-3.5, full-stack web technologies | Not explicitly reported | Auto-generates structured, ATS-friendly resumes, reducing preparation time | Placement-automation focus only; lacks career development and skill-gap analysis |
| [18] | Recommendation System for Resume Tracking and Job Suggestions | 2025 | Resume-job matching via generative AI and web scraping | Streamlit, PyPDF2, Generative AI, BeautifulSoup | Not explicitly reported | Automatically identifies skill gaps and recommends jobs using generative AI | Lacks integrated, end-to-end career guidance |
| [19] | Boost Your Career: Real-Time Job Analytics and Voice Feedback | 2024 | Collaborative-filtering based job analytics and resume-building interface | React.js, Tailwind CSS, Collaborative Filtering | Not explicitly reported | Simplifies resume creation with customizable templates and document generation | Focused on resume creation only; lacks AI-driven generation and job recommendation |

| Ref. | Paper / System | Year | Method / Approach | Technologies | Dataset | Key Findings | Research Gap / Limitations |
|---|---|---|---|---|---|---|---|
| [20] | Professional Resume Generation System | 2025 | Web dashboard providing employment-trend and in-demand-skill insights | PHP, Laravel, JavaScript, MySQL, Bootstrap, ML | User evaluation via Likert-scale survey | Rated 4.45 (functional suitability), 4.39 (reliability), 4.31 (performance efficiency) | Focused on resume generation/job notification; lacks integrated skill-gap assessment |

## V. RESEARCH GAP

### A. Fragmented Career Guidance Functionality

The primary limitation identified across the reviewed literature is that every system addresses only part of the needs of an individual seeking career guidance. While some studies develop tools for resume screening and recruitment [3], [8], [12], [17], others focus on job recommendation [9], [10], [18], personalized learning [15], or higher education [14]. A comprehensive approach would instead consider recruitment, skill-gap remediation through training, projects, internships, certifications, higher-education programs, scholarships and employment guidance together, allowing individuals to build their professional lives in a coordinated, step-wise manner. Current systems instead require users to operate multiple, disconnected tools.

### B. Limited Personalization and Holistic User Profiling

Most surveyed systems address only a partial set of the attributes relevant to career guidance — such as skills, certifications, projects, job interests, educational performance, labor-market trends and personal aspirations. The reviewed systems typically rely on a narrow set of attributes, such as RIASEC personality types [1], resume content alone [11], educational preferences [13], or competency profiles [7], limiting their ability to personalize recommendations for users with differing combinations of skills, competencies, education and aspirations.

### C. Dependence on Static and Domain-Specific Information Sources

Many systems base their recommendations on static information such as self-reported user data, internal knowledge bases, or historical recruitment records [1], [5], [6]. Such approaches are often ineffective in dynamic labor markets, where new employment areas emerge continuously and existing ones undergo structural change. Several solutions also operate within a single domain, limiting the flexibility and long-term relevance of the resulting career recommendations.

### D. Inadequate Career Development beyond Recruitment

The majority of reviewed systems focus primarily on recruitment, resume screening, or talent management [8]–[12], [17], [18]. While these are important functions, most solutions do not extend to internships, training, education, certifications and scholarships, limiting their usefulness to specific career stages rather than supporting a user through the full progression from education to employment and continued professional development.

### E. Limited Assessment, Benchmarking, and Validation

The practical impact of most reviewed solutions is validated only through limited user feedback, prediction accuracy, or recommendation-performance metrics [2], [8], [11], [15], [16], [20]. While informative, these metrics do not capture longer-term outcomes such as lifetime impact on the user, adaptability to changing preferences and market conditions, or general applicability across industries and career levels — leaving the surveyed systems without a consistent benchmark for career-planning effectiveness.

## VI. PROPOSED RESEARCH

Building directly on the gaps identified in Section V, this paper proposes ElevateHire, an integrated career-recommendation framework that unifies semantic resume analysis, intelligent job recommendation and skill-gap intelligence within a single recommendation pipeline. The framework applies Artificial Intelligence, Natural Language Processing, Machine Learning and Large Language Models to provide contextual job recommendation, personalized learning recommendation and explainable career guidance to support students through the full career-development process — directly addressing the fragmentation, limited personalization, static information dependence and narrow scope identified as gaps in the reviewed literature.

### A. Layer 1: Intelligent Resume Analysis and Candidate Profiling

The first layer performs resume understanding and candidate-profile generation. Candidates upload resumes in PDF or document form, which are automatically parsed using NLP techniques to extract structured data — education, technical skills, certifications, projects, internships, work experience and achievements. Named Entity Recognition (NER) and semantic analysis identify domain-specific competencies while reducing inconsistencies caused by variation in resume formatting. The extracted information forms a standardized candidate profile that underpins later recommendation steps. Unlike conventional ATS pipelines, which rely mainly on keyword matching, this semantic-profiling step captures the contextual relationships among a candidate's skills, experience and career interests, addressing the personalization gap identified in Section V-B.

### B. Layer 2: Semantic Job Matching and Skill-Gap Intelligence

The second layer performs intelligent career recommendation by semantically matching candidate profiles against job descriptions drawn from recruitment platforms and employment databases. Transformer-based language models and contextual embeddings capture the semantic relationship between candidate competencies and employer requirements, incorporating skills, experience, educational background and career interests rather than keyword overlap alone. The framework additionally performs dynamic skill-gap analysis, identifying competencies missing for a target role and recommending relevant courses, certifications,

learning resources and projects. In contrast to systems that stop at job matching, this layer unifies recommendation and personalized learning so that users can continuously improve their professional readiness — addressing the fragmented-functionality gap identified in Section V-A.

### C. Layer 3: Explainable Career Recommendation Framework

The third layer implements an Explainable Career Recommendation Framework that combines semantic resume assessment, job compatibility, skill-gap assessment and ATS-style resume assessment to compute an ATS Score. This assessment considers resume keywords together with skills, education, projects, certifications, internships and their compatibility with job requirements.

The resulting ATS Score indicates how well a candidate's resume aligns with current industry and recruitment expectations. Alongside the score, the system provides explanations covering well-matched skills, remaining skill gaps and recommended courses, certifications and projects for improvement. Rather than weighting individual keywords, the ATS Score is computed from the semantic similarity between the resume and selected job descriptions and the completeness of skills, experience, education and projects — offering an interpretable evaluation that also encourages continued professional development, addressing the benchmarking and explainability gap identified in Section V-E.

### D. System Architecture Overview

In the ElevateHire architecture, candidate resumes are accepted as input and processed using OCR and NLP techniques to extract structured candidate information. Transformer-based semantic matching then compares candidate skillsets, qualifications and experience against job descriptions and occupation knowledge bases. Skill-gap analysis, ATS compatibility scoring, job recommendation and adaptive learning-pathway generation are performed subsequently to enhance candidate employability. The output includes an intelligent candidate ranking and competency summary for recruiters, alongside personalized career, resume and learning suggestions for candidates. The framework's modular design allows its components to operate together as an integrated pipeline.

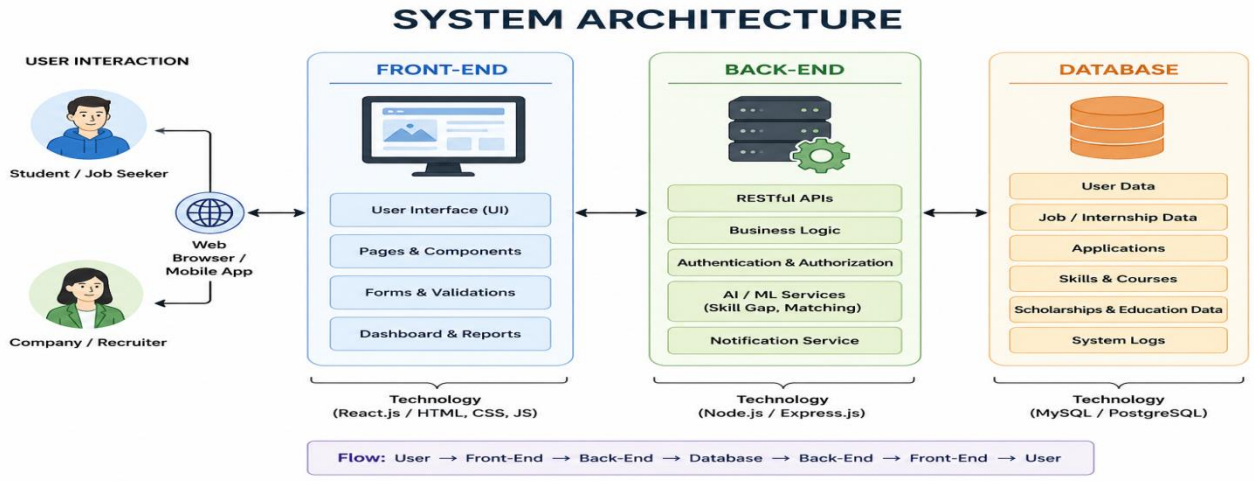


*Figure 1:Proposed system architecture of the ElevateHire framework, showing the resume-ingestion, semantic-matching and explainable-recommendation layers.*

### E. Expected Performance and Evaluation Strategy

The performance of ElevateHire is intended to be measured across five dimensions: career-recommendation accuracy (Top-1 and Top-3 rates, benchmarked against the 77.5% and 90.5% reported for Sankalp [2]); resume-analysis performance (benchmarked against the 91.4% accuracy reported for SATYA [8] and the 90.2% accuracy reported for Resume Ranker [12]); quality of skill-gap identification and learning recommendations (benchmarked against the 90% effectiveness reported for CareerCraft [16] and the 89.4% precision reported for the Bi-LSTM learning-path model [15]); job-recommendation efficiency, assessed through semantic-matching accuracy and recommendation relevance; and user satisfaction, benchmarked against the 4.71 satisfaction score reported for Sankalp [2]. This multi-dimensional evaluation strategy is intended to allow ElevateHire to be assessed both against systems that address individual aspects of career recommendation and against the career-development process as a whole.

## VII. DISCUSSION

The reviewed literature points to several consistent trends. AI-based recruitment and career-guidance research is progressively shifting from single-task, rule-based tools toward semantic, transformer- and LLM-based approaches capable of richer contextual understanding [2], [3], [6]. Skill-gap analysis and personalized learning recommendation are emerging as active research areas in their own right [5], [7], [15], and explainability is increasingly recognized as necessary for user trust in automated recommendations [6].

At the same time, the literature highlights recurring challenges: fragmentation across single-purpose tools (Section V-A), limited personalization arising from narrow attribute sets (Section V-B), dependence on static or domain-specific data in dynamic labor markets (Section V-C), a narrow focus on recruitment rather than the full career-development life cycle (Section V-D), and inconsistent benchmarking and validation practices across studies (Section V-E).

These trends suggest clear opportunities for future systems: combining semantic resume understanding with real-time labor-market intelligence [6]; integrating skill-gap analysis directly with personalized learning-path generation [7], [15]; and embedding

explainable-AI techniques so that recommendations are transparent to both candidates and recruiters. The real-world applications reported in the reviewed studies — resume screening and candidate ranking for recruiters [3], [8], [12], job discovery and matching for candidates [9], [10], and placement preparation and student support in academic settings [4], [14], [16], [17] — indicate that an integrated framework such as ElevateHire has practical relevance across both recruitment and educational contexts.

## VIII. CONCLUSION

### A. Summary of Findings

This paper has reviewed twenty recent studies on AI-based career counseling and intelligent recruitment, covering career recommendation, resume analysis, semantic matching, skill-gap identification, personalized learning and placement preparation. The review shows significant advances in the use of machine learning, NLP, large language models, generative AI, SBERT, BERT and related recommendation approaches for improving employability and recruitment outcomes. Career-recommendation frameworks such as [1], [2] and [13] have applied semantic techniques to deliver personalized guidance; resume-analysis and recruitment frameworks such as [8], [11], [12] and [17] have applied NLP and semantic-analysis techniques to resume evaluation; job-matching frameworks such as [9] and [10] have targeted recruitment efficiency; and further frameworks such as [14], [15], [16], [18], [19] and [20] address personalized learning and resume/recommendation generation.

The principal research gap identified across this literature is the absence of an end-to-end solution for career development. Most existing career-recommendation systems provide only partial coverage — career recommendation, resume analysis, job matching, recruitment, placement preparation, or personalized learning in isolation — rather than a single system guiding users from recognizing their interests and skills through to skill development, job recommendation and higher-education planning. The proposed ElevateHire framework is intended to address this gap directly through its integrated resume-analysis, semantic job-matching and explainable-recommendation layers, with the expected impact of providing a more transparent, holistic and continuously adaptive form of career guidance than the fragmented tools identified in this review.

### B. Future Scope

- Experimentation and validation: testing the proposed model on practical academic and recruitment data to evaluate recommendation accuracy, semantic-similarity performance and skill-gap-identification quality.
- Generative AI integration: incorporating advanced large language models and agentic AI to improve personalized career planning, resume optimization, interview preparation and explainable recommendations.
- Labor-market intelligence: augmenting the framework with real-time labor-market data to recommend relevant jobs, skills and higher-education opportunities.
- Industrial and academic partnerships: building collaborations with industry and universities to expand internships, projects, certifications, scholarships and mentorship opportunities.
- Explainable AI: further improving the transparency, explainability and ethical handling of privacy and security within the framework.
- Large-scale validation and benchmarking: deploying the framework at scale across domains, institutions and companies, and publishing standardized datasets and benchmarking results for future comparison.

## REFERENCES

[1] M. Roy and K. Sharma, "AI-Powered Career Guidance: A Scalable Model for Personalized Recommendations," IEEE Access, vol. 14, pp. 20927-20941, 2026.

[2] S. Nandi, M. Mohit, B. A. Nayak, and B. S. Babu, "Sankalp: AI-Powered Career Guidance System," IEEE Access, vol. 13, pp. 202376-202394, 2025.

[3] D. Peng, "Deep Learning-Driven Labor Education and Skill Assessment: A Big Data Approach for Optimizing Workforce Development and Industrial Relations," IEEE Access, vol. 13, pp. 111064-111086, 2025.

[4] G. W. Kim, W. H. Kim, K. Chung, and J. C. Kim, "Extraction of Meta-Data for Recommendation Using Keyword Mapping," IEEE Access, vol. 12, pp. 103647-103659, 2024.

[5] F. Gurcan and N. E. Cagiltay, "Big Data Software Engineering: Analysis of Knowledge Domains and Skill Sets Using LDA-Based Topic Modeling," IEEE Access, vol. 7, pp. 82541-82552, 2019.

[6] R. Alonso, D. Dessí, A. Meloni, M. Murgia, D. R. Recupero, and G. Scarpi, "A Seamless ChatGPT Knowledge Plug-in for the Labour Market," IEEE Access, vol. 12, pp. 155821-155837, 2024.

[7] S. Sengupta, S. Parab, S. Shetty, V. Nile, and A. Sambhaji, "Real-Time AI-Based Skill Gap Analysis and Adaptive Career Guidance Using a Generative AI Framework for the Modern Job Market," in Proc. 5th Asian Conf. Innovation in Technology, Pune, India, 2025, pp. 1-6.

[8] N. Bhavsar, S. Singla, D. Sharma, R. Dey, and S. Maji, "SATYA: Smart AI-driven Talent Yield Analyzer for Resume Screening and Recommendation Evaluation," in Proc. 4th Int. Conf. Robotics, Automation and Artificial Intelligence, Kharagpur, India, 2024, pp. 221-225.

[9] U. Ghosh, A. Roy, I. Bhattacharya, S. Sarkar, S. Ghosh, and S. Shandilya, "JobLinker: Automated Recruitment through Verified Intelligence," in Proc. Int. Conf. Artificial Intelligence, Computer, Data Sciences and Applications, 2026.

[10] N.Ghodichor, V. Patil, and S. Chhabria, "Elevating Recruitment Efficiency: The Role of MERN in Creating Career Bridge's Intuitive Job Platform," in Proc. IEEE Int. Conf. Artificial Intelligence and Quantum Computation-Based Sensor Applications, Nagpur, India, 2025.

[11] D. P. Daberao, G. Dalal, and R. Sreemathy, "ResumeInsight: An AI-Driven Framework for Semantic Resume-Job Matching and Skill-Gap Analysis," in Proc. Global Conf. Information Technology and Communication Networks, Belagavi, India, 2025, pp. 1-6.

[12] V. R. Pandian and S. Yugendran, "Resume Ranker for Freshers using NLP," in Proc. 7th Int. Conf. Innovative Data Communication Technologies and Application, 2025, pp. 902-907.

[13] K. Arora and R. Aggarwal, "A Novel Hybrid AI Framework for Career Path Recommendation Integrating SBERT Semantic Matching and TabTransformer for Structured Data," in Proc. IEEE 7th Int. Conf. Computing, Communication and Automation, 2025.

[14] M. Chowdhury and M. Rahman, "Blitz: A Student Life Goal Assistant Smartphone Application With Talent Hunt Program, Higher Study, Research, and Job Preparation Help Features," in Proc. 9th Int. Conf. Computational System and Information Technology for Sustainable Solutions, 2025.

[15] M. Shaikh and R. Purushothaman, "Deep Learning-Based Learning Path Recommendation System for Personalized Education," in Proc. 10th Int. Conf. Science Technology Engineering and Mathematics, 2025, pp. 1-6.

[16] S. T. Patil, R. Dugad, G. Akshata, P. Gyaneshwari, and S. Hatyalikar, "CareerCraft: Crafting Your Future, One Code at a Time," in Proc. 4th OPJU Int. Technology Conf., 2025.

[17] S. Priya K, S. M, J. I. Christy Abisha D, Saranya M, and Subalakshmi A, "Smart Campus Placement System: AI-Powered Resume Generation and Efficient Candidate Filtering," in Proc. 3rd Int. Conf. Sustainable Computing and Data Communication Systems, India, 2025, pp. 547-554.

[18] D. Gupta and P. Singh, "Development of a Recommendation System for Resume Tracking and Job Suggestions," in Proc. 3rd Ed. IEEE Delhi Section Flagship Conf., 2024.

[19] A. B. Cabrera, C. J. Centeno, M. A. S. Mercado, J. A. A. Miranda, R. C. Regala, and J. R. M. Tenio, "Boost Your Career: Real-Time Job Analytics, Virtual Voice Feedback and Job Notification using Collaborative Filtering Algorithms," in Proc. Int. Conf. Innovative Computing, Intelligent Communication and Smart Electrical Systems, 2024, pp. 1-6.

[20] S.Kanagamalliga, S. Rajalingam, R. Roshan, and N. M. Rohith, "A Professional Resume Generation System using Modern Web Technologies," in Proc. 4th Int. Conf. Applied Artificial Intelligence and Computing, 2025, pp. 1327-1332.

**Copyright & License:**
© Authors retain the copyright of this article. This work is published under the Creative Commons Attribution 4.0 International License (CC BY 4.0), permitting unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.