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An Explainable and Semantic AI-Based Applicant Tracking System

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ABSTRACT: Artificial intelligence's explosive growth in hiring and professional advancement has fundamentally changed how employability is evaluated and improved. The proposed system automatically analyzes resumes using NLP algorithms like Spacy and PyMuPDF that extract structured data about the candidates' skills, education, projects, and experience. It further makes use of machine-learning-based gap analysis and semantic similarity models, TF-IDF, and BERT, for the evaluation of candidature fit for specific job requirements and generates a Skill Match Score and Readiness Score. Apart from ranking, the platform extends individually customized learning path suggestions that close the identified gaps; hence, the advantages are extended to both recruiters and candidates. The major innovation is integrating Explainable AI, which provides understandable and clear reports on how rankings, scores, and recommendations are computed. Reviewing the literature on AI-enabled recruitment systems, the paper discusses the novelty of bringing together LLM-driven assessment with XAI-enabled interpretability into a single architecture of ATS.

KEYWORDS: Artificial Intelligence, Application Tracking System, Resume Parsing, Candidate Ranking, Explainable AI, XAI Reports, Skill Gap Analysis, Large Language Models, Semantic Matching, Employability, EdTech.

I. INTRODUCTION

The rapid digital transformation in the recruitment industry has resulted in organizations processing thousands of resumes every day, which has made manual screening inefficient, error-prone, and unsustainable for modern hiring needs [1] corporations and hiring agencies therefore rely on automated resume processing and information extraction systems to structure candidate data, reduce recruiter workload, and accelerate selection workflows [2]. Resume data, though semi-structured, varies widely in layout, format, and content which poses significant challenges for reliable parsing and structured extraction [4][8]. Besides, the big rush of online applications, often in hundreds for a single posting, makes candidate shortlisting a high-complexity problem needing intelligent computational support [11][12].

In order to automate this process, early ATS solutions concentrated on keyword-based filtering, simple machine learning categorization, and rule-driven parsing techniques[3][21]. Most of the modern approaches are based on leveraging NLP frameworks like spaCy, BERT, Word2Vec, TF-IDF, and cosine similarity for more accurate extraction of candidate attributes-skill, education, and experience[5][10][14][21]. Now deep learning models are incorporating multimodal input to improve the understanding of documents by leveraging layout and visual cues from resumes[11]. These innovations have also resulted in much faster parsing, standardized data generation, and algorithmic ranking of candidates for more scalable hiring pipelines [6][7].

But there are still a number of significant research gaps. Many ATS still depend on shallow keyword matching, which limits semantic interpretation of skill relevance, project impact, and contextual experience [7][18]. The biases also remain a critical challenge since automated ranking can inadvertently disadvantage underrepresented groups, yielding inequitable hiring outcomes [7]. Candidates should also tailor-fit their resumes for each posting by applying rigid ATS scoring strategies-which is time-consuming and not usually understandable for its reasoning [16].

Another point is that most current systems seldom provide transparent justification for their rankings or rejections; these are thus "black-box" decision mechanisms lacking in trust and accountability. Therefore, with AI playing a decisive role in such decisions, systems that ensure fairness, interpretability, and explainability become critical, in general [15][17]. While emergent LLM-driven recruitment optimization tries to cut human effort and improve candidate experience, explainable insights regarding score calculation and job-fit assessment remain underexplored [18]. Furthermore, very few works go beyond extraction and ranking to identify skill gaps or provide personalized career guidance, which is an important use case for improving employability outcomes.

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This paper suggests a unified concept of an AI-driven applicant tracking system (ATS) that not only retrieves and rates resumes but also provides an explanation for its choices and encourages ongoing candidate development in order to address these issues. The concept soothes the way for a more transparent hiring ecosystem in which recruiters and applicants alike can clearly understand how and why a ranking is assigned to a resume. Instead of rejecting applicants lacking specific competencies, the system detects missing competencies and predicts personalized learning pathways in order to bridge the gaps, making the hiring pipeline an opportunity pipeline. Our approach embodies semantic matching, interpretable analytics, and skill-gap-aware recommendations all in one framework turning automated hiring not only faster and data-driven but also fair, accountable, and career-supportive. This concept redefines the role of ATS from a filtering mechanism to that of an ethical, intelligent partner that enables employability.

II. LITERATURE REVIEW

2.1 Resume parsing and document pre-processing

Research on parsing resumes insists on the robustness in conversion from heterogeneous formats, such as PDF, DOCX, and HTML, into analysable text with segmentation into logical blocks: contact, education, experience, skills. Several of these systems perform with OCR and preprocessing pipelines to normalize different inputs before analysis [1][9][20]. The use of block- and segment-based extraction, such as through dictionaries, fuzzy matching, and chunkers, is recurrent for handling diverse headings and layouts [2][4][8]. Hybrid approaches that include regex on patterned entities such as email and phone number, lexicosyntactic parsing, and NER are general and effective to recover structured fields in noisy documents [5][6][10]. Multimodality approaches that incorporate visual/layout hints, such as font, bolding, position, enable better section segmentation than text-only methods with especial emphasis on format-sensitive resumes [11][19]. Finally, scalable implementations address big-data processing needs via distributed/text-analytics frameworks when resumes are to be processed at scale [9].

2.2 Entity extraction, representation and feature engineering

Accurate extraction of entities (names, skills, projects) underpins downstream matching and ranking. Modern systems use tokenization, POS tagging, and custom NER models trained or fine-tuned for resume domains[9][5][14]. Some works create domain word-embeddings or class-specific keyword sets to produce richer representations for resumes[12][21]. Topic modeling (LDA) has been applied as a complementary technique to capture higher-level thematic structure of resumes and generate interpretable features for scoring[14]. Feature engineering choices range from Elite Bag-of-Words to vector embeddings (TF/TF-IDF, Word2Vec, SBERT), each trading off interpretability and semantic richness [21][3][20].

2.3 Candidate matching, ranking and scoring approaches

Candidate-job matching in the reviewed literature spans classical similarity metrics to transformer-based semantic models. Cosine similarity of vectorized representations (TF-IDF, embedding vectors) remains a straightforward and widely used ranking baseline[10][22][3]. More advanced pipelines apply learned similarity via Skip-Gram embeddings or through ranking models to supervise alignment between resumes and job descriptions. [12][21] Topic-and score-based resume rating systems provide compact interpretable indicators for recruiters, for example numeric scores derived from LDA + NER. [14] Transformer models and BERT variants are reported to give superior contextual matching and ranking performance compared to keyword-only methods, enabling more nuanced job-fit assessment[11][18]. Pipelines that combine semantic matching with engineered attributes (experience, compensation, online presence) produce richer ranking signals used by recruiters[4][8].

2.4 Hybrid & multimodal systems, and LLM-driven pipelines

A trend observable in recent works is the shift toward hybrid and multimodal architectures that fuse layout, visual, and textual features in a better modelling of resume structure [11][19]. Hybrid approaches pair deep contextual encoders (BERT/Transformer) with rule-based or spaCy NLP modules; these combinations yield very good results on entity recall and robustness to idiosyncratic formats [5][16]. Separate but related work uses instruction-tuned LLMs in pipelines for resume generation, tailoring, and structured extraction — enabling resume refinement and job-specific tailoring without heavy task-specific training[16][17]. Interactive, user-facing platforms leverage LLMs, SBERT variants, or Llama-family models to provide resume scoring, chat-based guidance, and candidate-facing advice[20][16].

2.5 Explainability, fairness, and human-centered design in ATS

Empirical and conceptual works highlight that automation is not a guarantee of fairness and acceptance, while issues of transparency, trust, and procedural justice are paramount [7][15]. Perceived inaccuracies and applicant concerns, especially for minority groups, have been reported in user studies, entailing hybrid human-in-the-loop designs,

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confidence reporting, and selective parsing to increase perceived fairness [7]. Work on responsible ATS design argues for balanced training data, evaluation across subgroups, explainability features, and a detailed breakdown of why candidates are ranked this way [7][15][18]. Practical platforms have embedded score visualizations with actionable feedback, such as ATS compatibility scores and suggested improvements, that help applicants align resumes with job requirements [20][13].

2.6 Application systems, prototypes and deployment lessons

A number of papers present end-to-end systems and prototypes demonstrating real-world utility: web interfaces for upload + JSON extraction, dashboards for recruiters, job portals integration, and candidate portals for tracking applications[6][13][22]. Implementations show gains in processing speed, standardized storage (JSON, XML), and reduced manual effort for HR teams[6][22][12]. Commonly reported limitations include sensitivity to changes in input format, multilingual resume handling, and mitigations of possible hallucinations or over-generalizations when LLMs are used for generation tasks [5][16][20]. Practical recommendations involve modular architectures and continuous learning loops. Retrieval-augmented generation is one safety feature to lessen hallucinations [16][11].

2.7 Summary synthesis — converging observations and recurring limitations

Across the surveyed works there is strong convergence on several points preprocessing + robust segmentation are essential prerequisites for reliable parsing[1][2][4]. hybrid pipelines combining rule-based NLP and learned embeddings outperform single-strategy systems on diverse resume formats[5][11]. semantic models (BERT/transformers/embeddings) significantly improve matching quality over keyword matching[11][18], and practical systems benefit from recruiter-facing dashboards and candidate feedback mechanisms [6][20][13]. Nevertheless, common limitations persist format sensitivity and layout variability [19], limited multilingual coverage[9], lack of transparent scoring mechanisms[7][15], and the potential for algorithmic bias[7][15][18]. These gaps motivate integrated solutions that combine semantic matching, explicit explainability, and candidate development features (skill-gap suggestions) which is the conceptual thrust of this review.

III. METHODOLOGY

The proposed Explainable and Semantic Application Tracking System (ATS) is designed as a modular, transparent, and ethically interpretable employability intelligence framework. Unlike conventional keyword-based recruitment models, this system integrates semantic understanding, interpretability, and feedback-driven upskilling within a unified AI ecosystem.

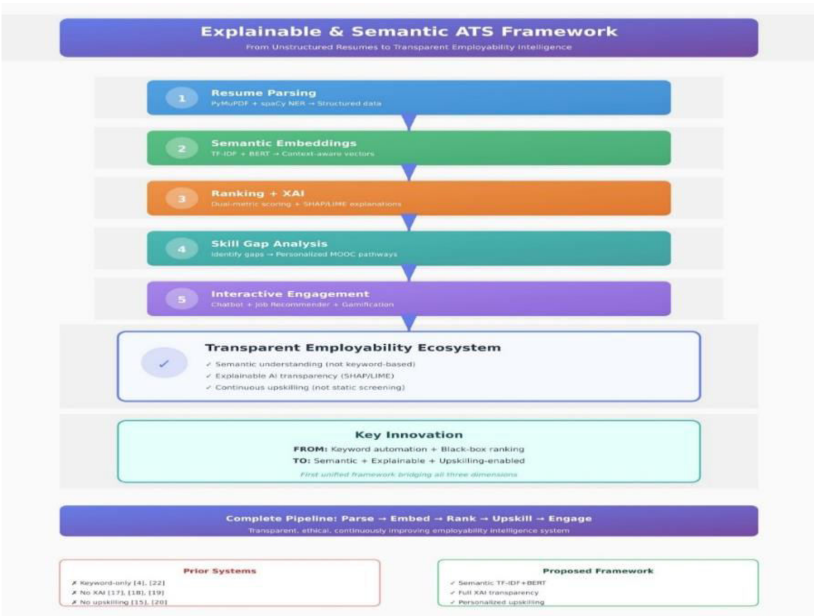

Figure1. The proposed Explainable & Semantic ATS Framework combining parsing, semantic embeddings, ranking, skill-gap analysis, and interactive modules for transparent and intelligent recruitment.

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3.1 Resume Parsing and Data Extraction

Any ATS pipeline's fundamental step is resume parsing, which converts unstructured resumes into machine-readable, organized formats. Earlier studies such as Abideen et al. The works by [4] and Mehboob et al. [22] utilized rule engines based on NLP and BoW models for keyword extraction. Although these approaches provided functional parsing, they were format-sensitive and resulted in semantic loss. Espinal et al. [19] propose a layout-enriched BERT model that effectively embeds layout and visual clues to enhance section segmentation, and Bhattacharjee et al. [16], and Pradeesh et al. [20] extract textual contents from resumes by using OCR and LLMs. However, these systems lacked robustness when handling diverse or stylistically complex resumes, especially scanned or graphically formatted ones. In the proposed system, resume parsing is achieved using a hybrid NLP–layout-aware pipeline. First of all, the extraction uses PyMuPDF with layout preservation for positional hierarchy. After that, spaCy-based NER extracts the structured attributes, including skills, experience, projects, education, and contact details. This dual-layer approach brings in both visual and linguistic intelligence, which ensures high recall along with cross-format adaptability. By integrating the robustness of [19] with the LLM contextual precision at [16][20], the proposed parsing module guarantees minimal format dependency and information loss to lay a valid foundation for semantic representation.

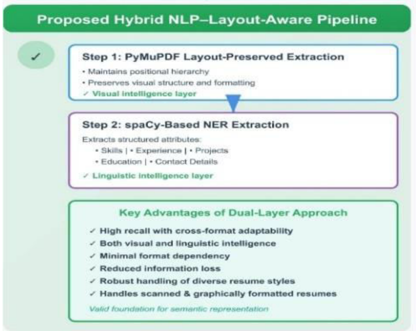

Figure 2. Hybrid layout-aware resume parsing pipeline using PyMuPDF extraction and spaCy NER for robust cross-format parsing.

3.2 Semantic Information Structuring

While works like Sharma et al. [21] (Elite BoW) and Mehboob et al. [22] used techniques for lexical similarity or frequency-based tokenization, these approaches completely ignored semantic context and polysemy. BERT-based semantic models, as proposed in [18] and further enhanced in [17], enhanced contextual understanding but remained non-transparent and computationally intensive, hence not interpretable.

The proposed system addresses these challenges through a hybrid embedding model that combines TF-IDF and BERT representations. Lexical weighting, represented through TF-IDF, captures relevance of terms, while the BERT embeddings bring in contextual semantics to make the model capture domain-specific dependencies, such as "backend developer" versus "data engineer". This hybridization allows for balanced precision and contextual depth that overcomes the keyword-centric constraints of [21] and the interpretability gap in [18]. Each of the resumes consists of structured JSON vector embeddings representing entities mapped to semantic clusters that align with job taxonomy standards. This structured semantic representation not only improves the accuracy of the ranking but also provides explainable tracing for each feature's contribution which was not achieved for any of the previous models [4][17][18][21][22].

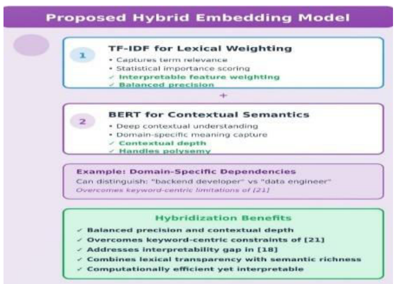

Figure 3. Hybrid embedding model combining TF-IDF for lexical weighting and BERT for contextual semantics to achieve interpretable and domain-aware resume representation.

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3.3 Candidate–Job Matching and Ranking

Candidate ranking forms a core analytical layer in ATS systems. Earlier approaches mainly employed deterministic or rule-based ranking mechanisms [4][22], or cosine similarity over lexical vectors [17][18], which give good precision, but with little interpretability, These systems also lacked interpretive analytics that explained why a candidate was ranked higher or which skill contributed most to selection.

The proposed framework introduces a dual metric ranking mechanism based on:

1. SMS: The degree of semantic overlap between job requirements and candidate attributes is shown by the Skill Match Score, which is calculated using hybrid embeddings, TF-IDF, and BERT.
2. The RS, or readiness score: It measures experience alignment, project diversity, and recentness to quantify job readiness.

Unlike the method in [4] and [22], the proposed approach dynamically learns the contributions of weights using an adaptive regression model. Additionally, XAI techniques such as SHAP and LIME show how each of the features, or skills, certifications, and domain experience, contribute toward the rankings, thus turning ranking from a black-box decision into an interpretable assessment. This will deliver recruiter trust and accountability for interpretability gaps [17][20].

Figure 4. Dual-metric ranking system combining Skill Match Score and Readiness Score with adaptive weighted aggregation for transparent and context-aware candidate evaluation.

3.4 Skill Gap Analysis and Learning Recommendation

While many of the earlier systems focused only on ranking, few addressed employability development. Hemalatha et al. [15] empirically established that AI-NLP, vision, automation, augmentation improves recruitment efficiency but did not look into personalized strategies of improvement. LLM-based systems such as [16] and [20] gave textual feedback for improvement of resumes but without structured identification of skill-gaps.

The proposed framework introduces an AI-driven Skill Gap Analyzer, which cross-compares the extracted resume embeddings against the ideal competency map of a given job description.

It flags missing or underrepresented skills and develops a personalized Learning Path Recommendation using prelinked MOOC or EdTech databases, such as Coursera and NPTEL. In contrast to [15] and [20], which take learning as some static advice, a closed-loop feedback mechanism is introduced whereby the updates on candidate progress recalibrate the readiness scores against time. This makes ATS a proactive upskilling engine from a simple passive filter-a capability that has not been imagined in any of the previous frameworks so far in [4][16][22].

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Figure. 5. AI-driven skill gap and learning engine identifying missing competencies, recommending personalized learning paths, and updating readiness scores through a closed-loop feedback mechanism.

3.5 Explainable AI (XAI) Transparency Layer

Explainability remains one of the most neglected areas in AI-based recruitment systems. While previous works like [17][18][19] used deep learning successfully, they did not provide any transparency into feature contributions or decision biases. The absence of interpretability has raised ethical concerns since candidates and recruiters often cannot understand and contest algorithmic outcomes The gap in this regard is being directly addressed by the proposed XAI module through SHAP and LIME visualizations. Skill Match and Readiness Scores are decomposed for each candidate to show which features drove their ranking. These reports are presented as XAI Dashboards: recruiters can audit ranking logic, while candidates can see transparent reasoning. This module embeds interpretability at both algorithmic and interface levels, hence ensuring trust, fairness, and accountability in decision-making, beyond the opaque structures of [16][20] Furthermore, the XAI layer conducts fairness diagnostics by examining the distribution of bias across gender, educational level, and experience patterns of applicants, along a dimension entirely unexplored in [4][15][17][18][22].

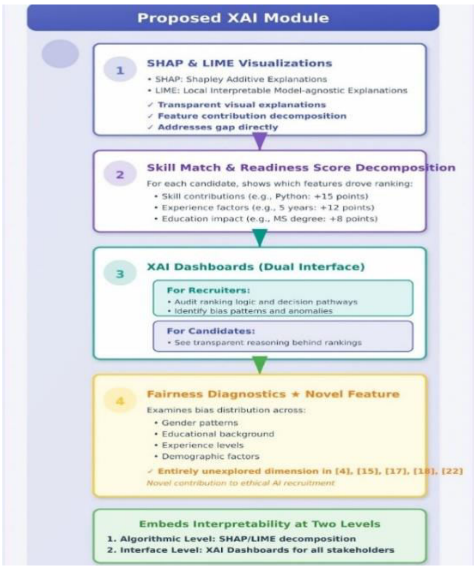

Figure. 6. Explainable AI module integrating SHAP/LIME visualizations, score decomposition, dual-interface dashboards, and fairness diagnostics for transparent and ethical candidate evaluation.

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3.6 Interactive Employability Intelligence Modules

The major novelty of the proposed framework is to embed mechanisms of interactivity and engagement that link analysis to action. In contrast, although systems like [16][17][20] engaged chatbots or LLMs to drive resume improvement instructions, the interactions there were one-way and without real context. The current system extends interactivity through three integrated modules:

1. Chatbot Resume Assistant: A conversational LLM in the line of GPT/Gemini, which explains ranking insights, XAI results, and personalized suggestions on how to optimize one's resume.
2. Role-Similarity Job Recommendation Engine: It suggests other job roles semantically similar to the current profile of the candidate, thus increasing the scope for job opportunities.
3. Gamified Skill Progress Tracker: It visually tracks candidate up-skilling via dynamic badges, scoreboards, and readiness milestones to provide a sense of achievement and continuous engagement.

This design makes the ATS shift from being merely a screening tool to a collaborative human-AI employability ecosystem, merging functionalities shown only partially in [16][17][20] and never cohesively integrated or explainable.

Figure 7. Three integrated interactive modules—LLM-powered chatbot assistant, role-similarity job recommender, and gamified skill progress tracker—designed to enhance candidate engagement and employability.

3.7 Comparative Summary and Methodological Integration

From keyword automation to semantic understanding, the evolution of AI-based recruitment systems is mapped across the literature [4][15][22], yet key gaps remain: explainability, fairness, and candidate development.

Although [19] has highly improved accuracy in segmentation and [18] introduces semantic embeddings, none of them offered interpretive transparency or learning-oriented feedback.

The proposed Explainable & Semantic ATS Framework bridges these limitations by integrating semantic matching (TF-IDF + BERT), XAI interpretability (SHAP/LIME), and personalized upskilling within a single, unified architecture. Every methodological module is directly aligned with previous innovations but systematically handles their deficiencies. The integration of this framework propels AI-driven recruitment further-from the automation of static decisions toward a transparent and ethical, continuously improving employability intelligence system aligned with the future vision of responsible AI adoption in the talent ecosystem.

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Figure. 8. Literature evolution and key gaps across prior ATS systems, with the proposed framework addressing all missing dimensions.

IV. CONCLUSION

Artificial Intelligence in recruitment has gone through evolution from rule-based resume screening to advanced data-driven employability intelligence. However, most existing Applicant Tracking Systems still lack solutions regarding interpretability, fairness, and personalized feedback. This paper reviewed, analyzed, and integrated insights from twenty-two significant studies that accentuate key research trends, limitations, and opportunities for innovation in AI-aided hiring.

The proposed Explainable and Semantic ATS Framework puts together an integral and ethical contribution toward bridging these gaps. It features layout-aware NLP parsing, hybrid semantic representation (TF-IDF + BERT), and dual metrics ranking (Skill Match Score and Readiness Score), enriched by XAI interpretability. Unlike typical systems, transparency, accountability, and fairness are emphasized in the framework; it provides traceable decision insights to recruiters and meaningful, feedback-driven learning paths to candidates.

Further, with the integration of LLM-based interactive engagement modules, such as the Chatbot Resume Assistant, Role-Similarity Job Recommender, and Gamified Skill Progress Tracker, the system goes even beyond selection into a dynamic, user-centric employability ecosystem. This layered architecture allows for frictionless hiring, continuous candidate development, and ethical recruiting practices, while optimizing the talent pool with data.

This study has shown how AI can transform recruitment from a transactional process into an equitable, interpretable, and continuously improving partnership of human and machine intelligence by embedding explainability and semantic reasoning in the design of ATS.

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