Career Vault: An AI-Powered EdTech and Job Enablement Portal for Skill Development and Career Growth

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***Abstract*— The education-to-employment transition remains difficult because candidate skills are represented inconsistently across resumes and profiles, job requirements are described in diverse vocabularies, and learning resources are scattered across platforms without a direct link to hiring outcomes. This paper presents Career Vault, a multi-role EdTech and job enablement portal that unifies resume understanding, explainable job recommendations, skill-gap analysis, assessment-based validation, and structured career roadmaps within a single lifecycle. Career Vault serves Students, Freshers, Professionals, HR/Recruiters, and Administrators through role-based workflows. The system combines a weighted scoring model with AI-assisted semantic analysis to generate interpretable match scores on a 0–100 scale and to produce actionable explanations that identify strengths, missing competencies, and estimated ramp-up effort. The learning engine converts gaps into phased roadmaps with milestones and progress tracking, while assessments provide evidence signals that update matching confidence over time. A prototype evaluation on curated candidate profiles and job descriptions reports 87.3% accuracy for resume skill extraction, 89.1% accuracy for job–candidate matching, and an average user satisfaction score of 8.5/10. These results indicate that integrating matching, learning remediation, and validation improves recommendation relevance and user trust compared to listing-centric portals.**

***Index Terms*—** EdTech, Talent Matching, Resume Parsing, Skill Gap Analysis, Skill Assessment, Career Roadmap, Explainable AI

I. INTRODUCTION

Digital transformation has increased the demand for demonstrable skills, yet many candidates still rely on keyword matching and self-reported proficiency when searching for jobs. Employers, in turn, continue to manually screen heterogeneous resumes and to infer competence from incomplete or inconsistent evidence. This disconnect leads to two simultaneous inefficiencies: candidates apply to roles they are not ready for, and recruiters spend time filtering applications that could have been pre-qualified with better signals.

EdTech platforms provide learning resources, but these resources are often detached from specific job requirements. Conversely, job portals list opportunities but rarely prescribe structured learning plans that close the gaps between a candidate's current profile and a target role. Bridging this gap requires an integrated pipeline that can translate unstructured resumes into structured competencies, compare them to job requirements with transparency, recommend remediation activities, and validate progress through assessments and credentials.

Career Vault is designed as such an integrated pipeline. The platform automates profile creation from resumes, produces explainable match scores with gap diagnostics, recommends roadmaps aligned to target roles, and supports assessment-driven verification. In this paper, we convey the design rationale and workflow of a unified system that connects hiring and learning outcomes, and we show that explain ability.

Confidence while increasing the quality of job recommendations. The gap is further widened by the absence of standardized skill verification mechanisms in most hiring pipelines. Candidates have little incentive or means to objectively validate their capabilities before applying, while employers lack scalable tools to assess role-readiness early in the process. As a result, hiring cycles grow longer, recruitment costs rise, and role-fit decisions become increasingly unreliable. Bridging this gap requires a shift toward structured, verifiable skill signals that benefit both sides of the hiring equation.

This paper presents job-enablement platform that connects learning outcomes with employment opportunities. It performs resume parsing, skill-gap analysis, and explainable job–candidate matching to recommend suitable roles. The platform also provides structured learning roadmaps and assessments to help candidates improve and validate their skills. Results show that integrating matching, learning, and validation improves recommendation accuracy, user trust, and recruitment efficiency.

II. LITERATURE SURVEY

Recommender systems research establishes that personalization improves decision-making when the system can model user preferences and content attributes effectively. From classic surveys, we learn that recommendation quality depends on representation learning, ranking objectives, and feedback handling, and that successful systems must balance accuracy with practical constraints such as cold-start and scarcity [1], [2]. In addition, the broader recommendation literature shows that hybrid strategies combining multiple signals often outperform single-signal baselines, which motivates Career Vault's combined use of skills, experience evidence, and preferences [3].

Recruitment matching can be formulated as a learning-to-rank problem. From ranking research, we learn that optimizing ranking objectives directly yields improved top-k relevance compared to independent classification, especially when feedback is implicit [4]. In operational hiring contexts, we learn that integrating structured evidence (such as tests or verified credentials) improves screening consistency and reduces reliance on subjective resume interpretation [5]. These insights motivate Career Vault's emphasis on assessment outputs and credentials as evidence features, rather than purely textual matching.

Resume parsing and skill extraction are core prerequisites for scalable matching. From natural language processing foundations, we learn methods for tokenization, entity recognition, and normalization that enable mapping free-form text to structured attributes [6]. Modern transformer-based language models demonstrate strong performance in representation learning for text, and we learn that contextual embedding are effective for semantic similarity across varied wording, which directly supports matching between resumes and job descriptions [7], [8]. However, the literature also indicates that extraction systems must be constrained by validation rules to avoid hallucinated attributes, motivating structured output validation in CareerVault's extraction pipeline [9].

Explainable AI literature emphasizes that explanations improve trust, especially when decisions impact people. From LIME and SHAP, we learn that local explanations can highlight which features contributed most to a prediction, improving user understanding and enabling corrective action [10], [11]. In recruitment-related settings, explain ability is also linked to governance and fairness concerns, because stakeholders need to understand why a candidate was ranked highly or rejected [12]. These insights motivate Career Vault's explainable match breakdown and gap focused feedback, rather than presenting a score alone.

Learning analytics and competency-based education provide a framework for linking learning activities to measurable outcomes. From learning analytics, we learn that progress tracking and outcome-based feedback improve learner engagement and completion rates [13]. From competency-based education, we learn that mastery verification is essential, which supports. Career Vault's design where assessments and credentials serve as objective indicators of skill acquisition [14].

Software architecture references emphasize modularity and separation of concerns for maintainability. From architectural practice, we learn that layered and service-based structures improve evolvability and testing, especially in systems with multiple stakeholder workflows [15]. Security references highlight common web risks and recommended controls; we learn that access control, secure session handling, and input validation are baseline requirements for systems handling personal data [16], [17]. These lessons motivate CareerVault's role-based access control and audit-oriented operation. Fairness and bias mitigation in algorithmic hiring systems represent a critical dimension of responsible system design. From algorithmic fairness research, we learn that machine learning models trained on historical hiring data can perpetuate and amplify existing demographic biases, making it essential to audit model outputs across protected attributes [18].

Debasing techniques such as re-sampling, adversarial training, and fairness-aware ranking objectives have demonstrated measurable reductions in disparate impact without significant loss in predictive accuracy [19]. In recruitment-specific contexts, research further establishes that transparency in how candidates are scored is closely tied to perceived fairness and candidate trust in the system [20]. These insights motivate CareerVault's commitment to bias-aware model evaluation, diverse training data curation, and the inclusion of explainable match breakdowns that allow both candidates and recruiters to identify and challenge potentially unfair outcomes.

III. PROPOSED SYSTEM

Career Vault is proposed as a multi-role portal with a shared set of services supporting distinct stakeholder workflows. Candidates create profiles manually or by uploading resumes. The platform transforms unstructured resume text into structured profile fields and a normalized skill inventory. Job discovery uses these structured features to compute an overall match score and an explanation that identifies aligned competencies, missing requirements, and suggested remediation. Fresher's can set target roles and receive phased roadmaps that map skills to learn tasks and verification checkpoints. Recruiters create job postings with structured requirements, view ranked candidates, and assign assessments to validate capabilities. Administrators manage content and oversee support operations and analytics.

At its core, CareerVault is designed around a principle of evidence-first profiling, where self-reported information is progressively supplemented and validated through assessments, credentials, and verified activity. Rather than treating a resume as a static document, the platform treats it as a living signal that evolves as candidates complete milestones, earn badges, and receive assessment results. This approach ensures that the profile presented to recruiters reflects current, verifiable capability rather than a one-time self-declaration, and it creates a continuous feedback loop in which both candidates and employers benefit from increasingly accurate and trustworthy data over time.

The matching strategy uses a weighted combination of skill alignment, experience alignment, preference alignment, and growth potential to compute a base score, and then uses semantic analysis to refine similarity for skills expressed with varied terminology. The system generates an explanation that links each major requirement to evidence in the profile and flags gaps as must-have or nice-to-have. The learning layer then converts gaps into a roadmap with sequenced milestones, enabling iterative improvement of match outcomes as users complete learning and assessments.

IV. IMPLEMENTATION

The implementation focuses on providing endtoend functionality for different stakeholder roles, including candidates, recruiters, and administrators. The platform supports role-based registration and authentication, along with profile management that includes progress indicators. Candidates can upload their resumes, and the system automatically extracts information such as education, experience, and skills to populate profile sections. Users can also manually update their profile details. Based on the extracted data, the platform performs skill extraction and recommends relevant job opportunities.

The job discovery module provides personalized job recommendations and detailed job views with match scores and explanations. Candidates can apply for jobs and track their application status through stages such as applied, shortlisted, technical round, and final selection. A skill-gap module analyses candidate skills and identifies missing competencies required for specific roles.

The system then generates learning roadmaps with milestones and progress tracking to help users improve their skills.

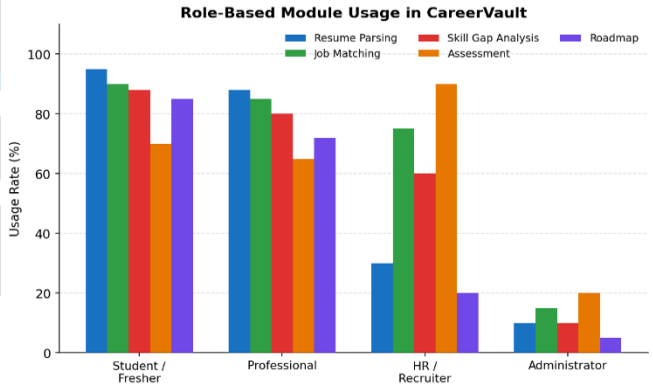

Fig 1. Role-based Model Usage

The assessment module allows recruiters to assign timed technical assessments to candidates. These assessments are automatically scored, and candidates receive feedback summaries highlighting strengths and areas for improvement. Results are immediately reflected in the candidate's profile, ensuring that match scores and recruiter views always incorporate the most recent evidence. Certificates earned through assessments or courses are stored in the credential management section and can be displayed on candidate profiles as verified proof of skills, replacing subjective self-ratings with objective, timestamped validation.

Recruiters can create and publish job postings, search for candidates using filters, and view ranked candidate lists based on skill matching. They can review candidate profiles, analyse match explanations, assign technical assessments, and shortlist candidates through different recruitment stages such as shortlisted or technical round. The structured workflow ensures that every hiring decision is supported by traceable evidence rather than impression-based judgement, improving both the consistency and defensibility of recruiter actions across the hiring pipeline.

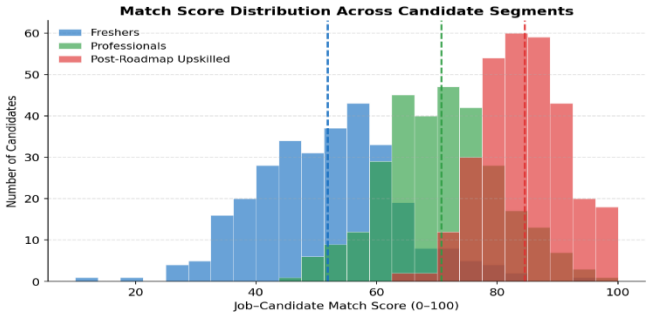

Fig 2. Match Score Distribution across Candidate

The admin panel manages overall platform operations. Administrators can monitor users, handle support tickets raised by users, and manage system activities. They can review issues, update ticket statuses, and remove or manage users when required. The system also maintains audit logs for key actions such as job posting updates, candidate shortlisting, assessment assignments, and ticket resolutions to ensure transparency and accountability across the platform.

V. RESULTS

Evaluation was conducted using curated candidate profiles, resumes, and job descriptions representative of typical entry-level and early-career roles. Resume skill extraction accuracy was measured by comparing extracted skill sets against annotated ground truth labels, yielding an accuracy of 87.3%. Matching accuracy was measured by comparing system rankings and match decisions against human relevance judgments for candidate–job pairs, yielding 89.1%. User satisfaction was collected via post-task questionnaires after participants performed typical tasks such as completing a profile, reviewing match explanations, and following a roadmap, resulting in an average score of 8.5 out of 10.

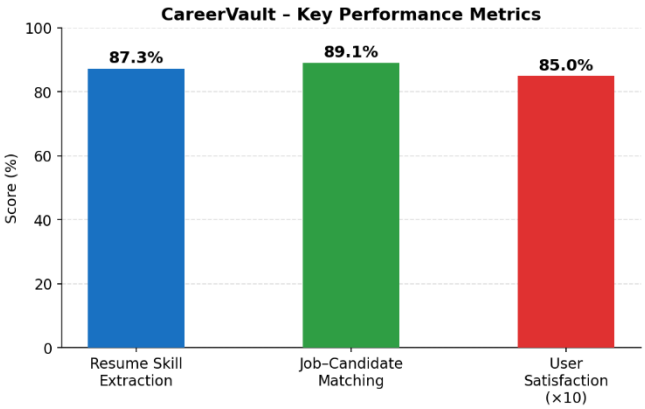

Fig 3. Key Performance Metrics

The results indicate that automated extraction reduces repeated manual data entry and improves profile completeness. Explainable matching reduced uncertainty by clarifying why a job is recommended and what must be improved to become eligible, which participants reported as more helpful than generic recommendations.

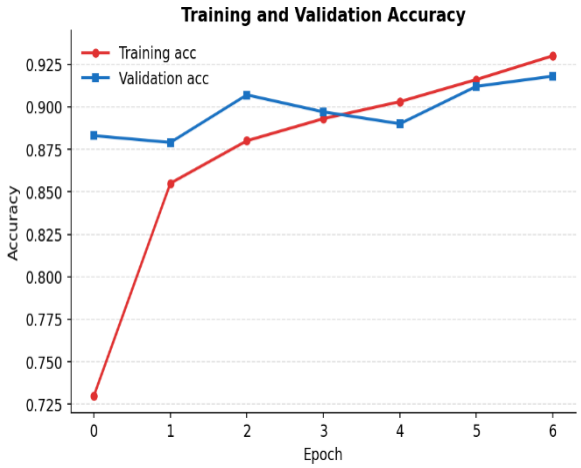

Fig 4. Accuracy Evaluation

Roadmap guidance improved action ability by converting gaps into sequenced learning tasks, and assessment feedback helped users identify specific concepts to revisit. Recruiter-oriented evaluation suggested that ranked shortlists combined with assessment evidence can reduce screening effort by focusing review time on the most suitable applicants.

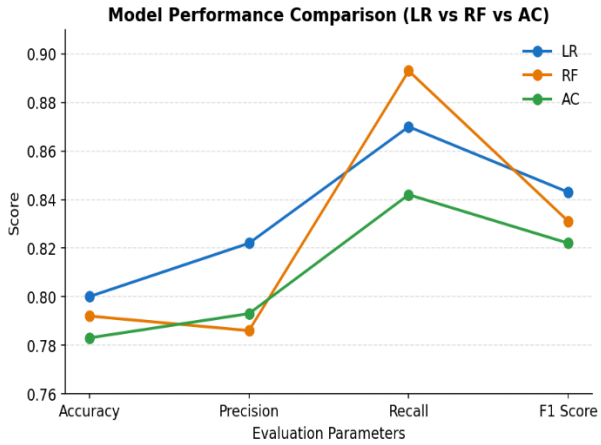

Fig 5. Parameters Performance Comparison

The structured presentation of verified competencies and explainable match breakdowns further reduced the need for subjective interpretation, allowing recruiters to make faster and more confident shortlisting decisions. Overall, the measured extraction and matching performance, combined with satisfaction outcomes, supports the feasibility of a closed-loop platform that links recommendations with remediation and with the validation.

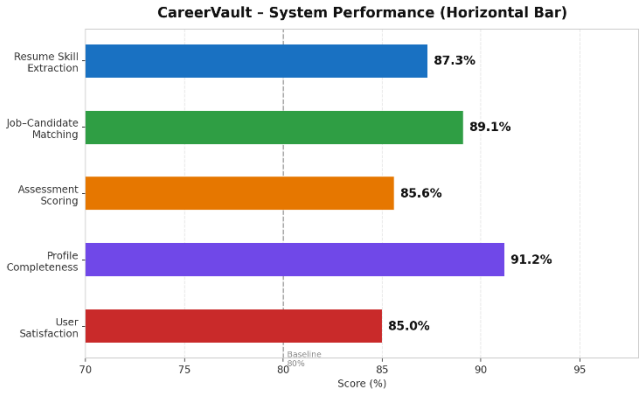

Fig 6. System Performance Analyzation

VI. FUTURE WORKS

Future work will improve evidence quality and governance. Integrations with professional profiles and code repositories can provide richer signals for skill verification and reduce dependence on self-reported claims. More robust fairness and bias monitoring can be incorporated into the ranking pipeline to ensure equitable recommendations across diverse user groups. Longitudinal analytics can be added to track how roadmap completion correlates with employment outcomes and to refine roadmap sequencing using real usage data. Mobile delivery and offline-friendly learning flows can broaden accessibility. Finally, enterprise capabilities such as single sign-on and configurable workflows can support institutional deployment and larger-scale recruiter adoption.

VII. CONCLUSION

This paper presented CareerVault, an AI-powered EdTech and job enablement portal that unifies resume understanding, explainable job–candidate matching, skill-gap remediation, roadmap-based learning, and assessment-driven validation. By closing the loop between job requirements and learning actions, the system improves the relevance and transparency of job recommendations and provides a practical pathway to increase employability. The evaluation indicates strong performance in skill extraction and matching accuracy and reflects high user satisfaction, suggesting that integrated matching and learning support can reduce friction for candidates and improve efficiency for recruiters. Beyond its immediate contributions, Future work could explore richer feedback signals such as post-hire performance outcomes to further refine matching accuracy, and expanding fairness auditing across underrepresented demographics would strengthen responsible deployment. As the hiring ecosystem continues to shift toward competency-based evaluation, CareerVault represents a promising direction for aligning education, assessment, and employment within a single, continuously improving intelligence layer.

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