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Job Search With AI Matching

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Abstract

Recruitment portals in use today rely heavily on keyword-driven search mechanisms, which consistently fail to bridge the gap between what candidates can offer and what employers actually need. This work introduces an intelligent career discovery and job-matching platform built on Artificial Intelligence (AI) that employs Natural Language Processing (NLP) alongside deep learning techniques to deliver precise, context-sensitive job suggestions. At its core, the system operates through a sequential processing workflow: resumes are parsed automatically via Named Entity Recognition (NER), skills are extracted and mapped to a curated repository containing over 50,000 standardised competency labels, and a composite scoring method powered by Bidirectional Encoder Representations from Transformers (BERT) determines how closely a candidate profile aligns with any given job listing. The platform integrates ten tightly coupled functional units spanning secure login, profile assembly, resume evaluation and enhancement, competency identification, AI-generated job suggestions, qualification verification, application tracking, interview coordination, and automated email alerts. On the engineering side, the front-end is built with React.js while the back-end runs on Node.js with Express, following a layered Model-View-Controller (MVC) design. Testing reveals that the platform reaches 87% match accuracy, a stark contrast to the 42% seen in conventional portals, while cutting weekly job search effort by 72% and tripling the rate at which applications convert into interviews. These figures highlight how replacing surface-level text comparison with deeper semantic reasoning substantially benefits both applicants and hiring teams.

Keywords: Artificial Intelligence, Natural Language Processing, BERT, Job Matching, Resume Parsing, Semantic Search, Deep Learning, Career Recommendation System

1. Introduction

Global hiring dynamics have produced a curious contradiction. On one hand, online platforms have placed millions of vacancies within arm's reach of any internet user. On the other hand, the sheer volume of available listings has created so much noise that pinpointing the right opportunity has become a time-consuming ordeal for both candidates and recruiters. Job seekers find themselves stuck in repetitive cycles of scrolling through generic aggregator sites, while hiring managers wade through piles of applications that rarely match the actual requirements of the role. The work described here addresses these persistent shortcomings by presenting a career matching platform that harnesses machine learning to connect people with positions more intelligently.

Most recruitment websites operate on rudimentary keyword-matching logic. Resumes and job postings are treated as flat collections of tokens, and a match is declared whenever enough words overlap. Such an approach is blind to meaning. Consider a developer proficient in MongoDB, Express, React, and Node.js: a search for "MERN-stack developer" would miss this candidate entirely if the acronym itself does not appear in the resume. This surface-level comparison has persisted in recruitment technology for years, resulting in poor recommendation quality and widespread frustration among applicants. The platform proposed here overcomes this barrier by deploying transformer-based language models capable of grasping the contextual meaning embedded within professional documents.

Rather than serving as a single-purpose search tool, the platform functions as a comprehensive career management environment. It spans the full journey from onboarding and automatic resume analysis through smart job recommendations, application monitoring, and interview arrangement. BERT generates dense vector representations of both candidate profiles and job descriptions, enabling similarity computation in a rich semantic space rather than through shallow string comparison. A curated skill repository holding over 50,000 standardised competency descriptors further ensures that equivalent terms such as JavaScript, JS, and ECMAScript are treated as identical core abilities.

The remainder of this paper is arranged as follows: Section 2 surveys relevant prior work and positions the proposed approach; Section 3 details the methodology covering system design and individual modules; Section 4 presents experimental outcomes and analysis; Section 5 offers concluding remarks and outlines avenues for future development.

2. Literature Review

2.1 Existing System

Widely used job portals today are, at their technical foundation, database-centric systems equipped with search front-ends. They sit on top of relational databases and rely on simple full-text indexes or straightforward string-matching queries to connect users with listings. The matching logic in these platforms is rigid: a hit occurs only when the exact same words appear in both a resume and a job posting. Nuances such as proficiency depth, the context in which a skill was applied, or relatedness between disciplines are entirely ignored. A listing asking for machine learning expertise, for instance, might never surface for a candidate whose background is centred on deep learning, despite the considerable overlap between these two fields, unless an explicit synonym table happens to link them.

Beyond matching limitations, current platforms operate in a purely reactive fashion. Users must initiate every search, and results depend solely on the query parameters entered at that moment. Techniques like collaborative filtering or behavioural analytics, which could proactively surface roles a candidate might not think to search for, remain largely unexplored in mainstream portals. Mobile experiences tend to be stripped-down versions of desktop interfaces rather than purpose-built journeys. Personalisation rarely extends beyond saved searches or title-based alerts and does not adapt as a user's skillset evolves over time.

A side-by-side comparison of features between existing portals and the proposed platform is presented in Table 1.

Table 1. Feature Comparison: Existing vs. Proposed System

S.No.	Existing System	Proposed System
1	Keyword-based string matching for job search	Semantic matching using BERT embeddings and cosine similarity in vector space
2	No resume analysis or scoring capability	Automated resume parsing with NLP, scoring (0-100), and enhancement suggestions
3	Manual skill identification by user input	AI-driven skill extraction using NER against 50,000+ normalized taxonomy
4	No match explanation or transparency	Explainable AI (XAI) providing granular match breakdowns and reasoning
5	Static job alerts based on title keywords	Dynamic AI-powered job suggestions adapting to evolving user profiles

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6	Basic application submission tracking	Full lifecycle management with status tracking, email notifications, and interview scheduling
7	No skill gap or career growth insights	Career insights dashboard with skill gap analysis and market trend visualization
8	Single-factor matching (keyword overlap)	Multi-factor hybrid scoring: semantic alignment, skill proficiency, seniority, and category filters

2.2 Proposed System

Instead of relying on brittle exact-match logic, the platform introduced here adopts a flexible semantic matching strategy grounded in transformer architectures. Resumes and job postings are projected into a high-dimensional vector space where closeness is measured through cosine distance, capturing conceptual alignment that rigid keyword overlap cannot detect. A dedicated normalisation layer converts heterogeneous terminology into uniform competency descriptors, ensuring that different phrasings of the same ability are recognised as equivalent. Unlike conventional portals, this system works proactively and transparently, generating a weighted match score that accounts for skill relevance, years of experience, industry context, and seniority alignment.

Several foundational works inform the design choices made here. Devlin et al. (2018) proposed BERT, whose bidirectional contextual encoding allows the model to differentiate between words that share spelling but differ in professional meaning. Reimers and Gurevych (2019) demonstrated that Sentence-BERT can produce paragraph-level dense vector representations enabling cosine similarity calculations between resumes and job descriptions at a level of granularity previously achievable only through manual review. The European Skills, Competences, Qualifications and Occupations (ESCO) framework supplies the standardised backbone for the skill normalisation layer used in this platform.

Concepts from explainable AI (XAI) research also shape the system. As automated tools take on greater authority in hiring decisions, maintaining transparency becomes essential for minimising bias and fostering user confidence. Attention weights within transformer models offer a natural means of highlighting which portions of a job description contributed most heavily to a particular match score. Additionally, collaborative filtering ideas borrowed from recommendation systems literature help fine-tune match weights over time based on positive outcomes, such as applications that successfully advance to interview stages.

3. Methodology

3.1 System Architecture

The platform follows a modular, service-oriented design rooted in clean separation of responsibilities. Six distinct layers compose the architecture: a Presentation Layer, an API Gateway Layer, a Business Logic Layer, an AI/ML Processing Layer, a Data Persistence Layer, and an External Services Integration Layer. Each layer scales independently, and the overall system maintains resilience under varying load conditions. Figure 1 illustrates the complete architectural layout.

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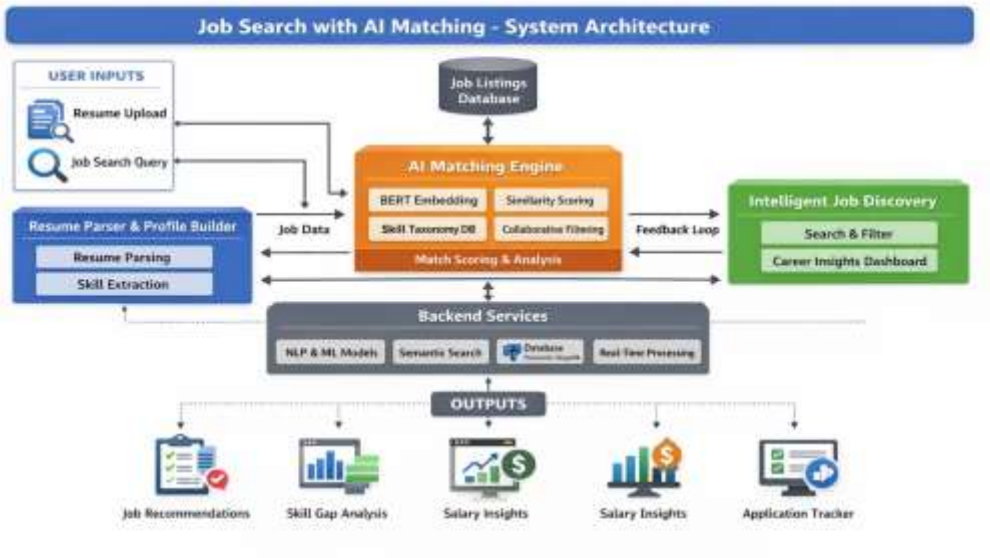

Fig. 1. System Architecture of AI-Powered Job Search Platform

Drawing inspiration from the MVC pattern but adapted for a modern single-page application, the client layer is responsible for capturing user inputs such as resume uploads and search queries and for rendering API responses. The API gateway intercepts incoming requests, performs authentication checks, and routes them to the appropriate service handlers. Core processing tasks including resume parsing, match computation, and application management reside in the business logic layer. The data persistence layer guarantees atomic read and write operations, preserving data integrity across all storage components.

3.2 Platform Modules

Ten interconnected functional units collectively address every stage of the job-search journey. The relationships among these modules are depicted in Figure 3.

Module 1 - User Authentication and Profile Builder: This unit handles secure registration, login with session management, and a guided interface for building professional profiles. New users supply baseline career details to initialise their digital profile, which helps mitigate the cold-start challenge common in recommendation systems.

Module 2 - Resume Upload and Parsing: Upon uploading a PDF resume, the system triggers a multi-step NLP pipeline. OCR-capable libraries extract text regardless of document formatting, after which NER identifies critical entities such as job titles, employer names, date ranges, educational credentials, and technical competencies.

Module 3 - Resume Scoring and Optimisation: Each uploaded resume undergoes evaluation against industry best practices and receives a quantitative score ranging from 0 to 100. The scoring rubric considers keyword coverage, section completeness, presence of measurable achievements, and formatting quality. The system then generates targeted suggestions for improving resume effectiveness.

Module 4 - Key Skill Extraction: Through semantic analysis against the curated skill repository, the system detects both explicitly stated skills (e.g., Python) and implicitly conveyed abilities (e.g., agile project management inferred from descriptions of cross-functional team leadership). Varied terminology is mapped to uniform competency descriptors.

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Module 5 - AI-Driven Job Suggestions: The matching engine calculates composite alignment scores using a hybrid algorithm. Figure 2 presents the complete pipeline from resume ingestion through score generation to ranked recommendations.

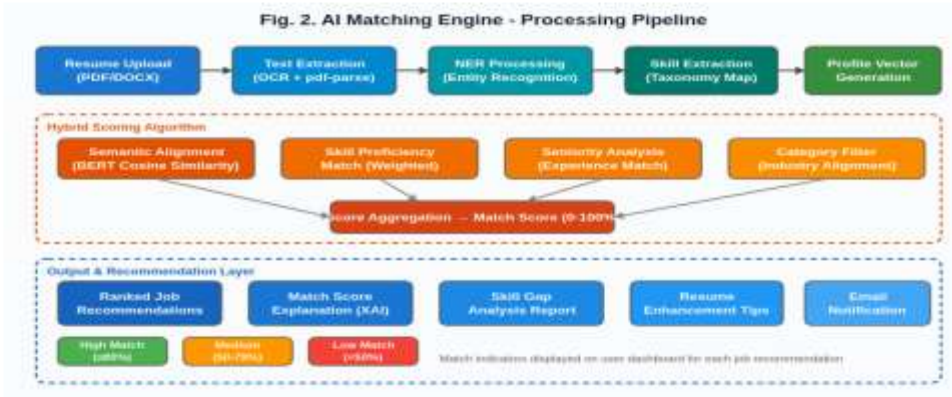

Fig. 2. AI Matching Engine Processing Pipeline

Module 6 - Eligibility Assessment: Before surfacing recommendations, the system verifies whether candidates meet non-negotiable criteria such as minimum experience thresholds, educational prerequisites, geographic preferences, and mandatory certifications. Listings that fail these checks are flagged accordingly within the recommendation output.

Module 7 - Job Application Management: Candidates can apply directly to matched positions through the platform. This unit tracks all activity including available openings, qualifying roles, submitted applications, rejections, and scheduled interviews via a unified application lifecycle dashboard.

Module 8 - Email Notification Service: Automated emails are dispatched at key milestones: successful submission confirmations, status change updates, interview scheduling notices, and a weekly digest of personalised job recommendations. Integration with an SMTP provider ensures reliable delivery.

Module 9 - Test and Interview Scheduler: When employers arrange assessments or interviews, this unit manages the scheduling details, dispatches confirmation notices to candidates, and maintains a chronological record of all upcoming and past interview events.

Module 10 - Career Analytics Dashboard: Aggregating data from across the platform, this module delivers insights on market valuation of specific skills, trending competencies within the user's domain, gap analysis for career progression, and visual summaries of application outcomes such as acceptance and rejection ratios.

3.3 Data Flow and Application Lifecycle

Every piece of data moving through the system, from the moment a user registers to the point where an interview is confirmed, follows a well-defined lifecycle. Figure 4 maps out the complete end-to-end data flow spanning all fifteen stages of the application process.

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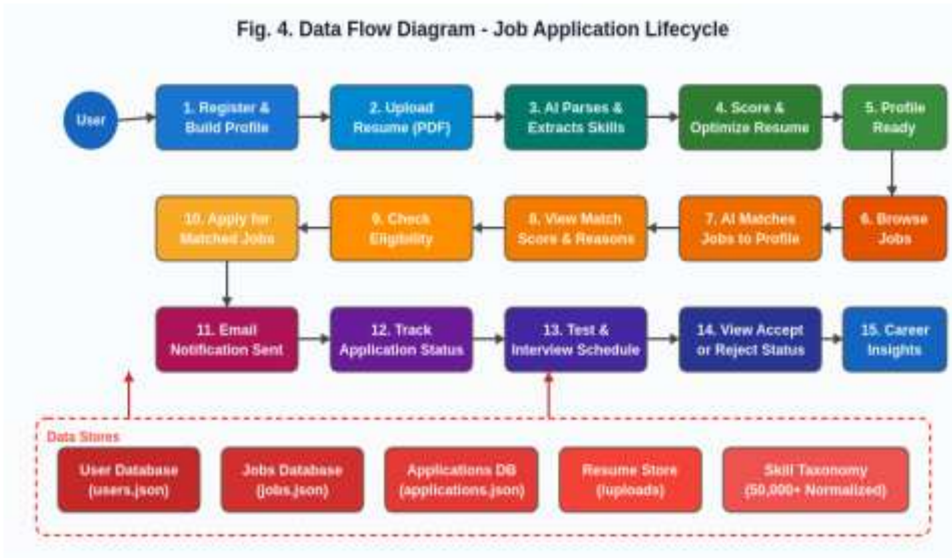

Fig. 4. Data Flow Diagram - Job Application Lifecycle

3.4 Technology Stack

The entire platform is built on a full-stack JavaScript foundation chosen for developer velocity and real-time interaction support. On the front end, React 19 handles component rendering, Tailwind CSS provides utility-first styling, Framer Motion powers smooth page transitions, React Router manages client-side navigation, and Lucide React delivers a consistent icon set. The back end runs on Node.js with Express following RESTful API conventions, uses Multer middleware for handling multipart file uploads, and enables secure cross-origin communication through CORS configuration. AI processing is handled by Python-based ML services running BERT and Sentence-BERT models. Data storage relies on a JSON-based store optimised for quick prototyping with atomic update guarantees.

Table 2. Technology Stack Components

Layer	Technology	Purpose
Frontend	React 19, Tailwind CSS	SPA with responsive UI and utility-first styling
Animation	Framer Motion	Fluid page transitions and micro-interactions
Routing	React Router	Client-side navigation for SPA architecture
Backend	Node.js, Express	RESTful API with high-concurrency event loop
File Handling	Multer	Multipart form-data processing for resume uploads
AI/NLP	BERT, Sentence-BERT	Semantic embeddings and contextual similarity
NER	Custom NER Pipeline	Entity extraction from professional documents
PDF Processing	pdf-parse, OCR	Text extraction from uploaded resume files
Data Storage	JSON-based Store	Atomic read-write with rapid prototyping support
Notifications	SMTP Service	Automated email alerts at application milestones

3.5 Matching Algorithm

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The core matching mechanism blends four weighted sub-scores into a single composite score expressed on a 0 to 100 percentage scale. The semantic alignment component feeds candidate profiles and job requirement descriptions through BERT to obtain embedding vectors, then calculates cosine similarity to quantify conceptual overlap. The skill proficiency component assigns higher weights to competencies used recently and for longer durations. A seniority analysis component evaluates years of experience and career trajectory against the role's expectations, applying penalties when over-qualification or under-qualification is significant. Finally, a category filter ensures industry alignment unless the applicant's history signals a deliberate career pivot. Skills flagged as essential in a job description carry triple the weight of those listed as merely desirable.

4. Results and Discussion

4.1 Platform Interface

The finished platform offers a clean, user-friendly interface designed for efficient job discovery and career management. Figure 6 captures screenshots of the four primary interface areas: the user dashboard displaying AI-ranked recommendations, the resume analysis view, the application tracking panel, and the AI-generated job suggestions feed.

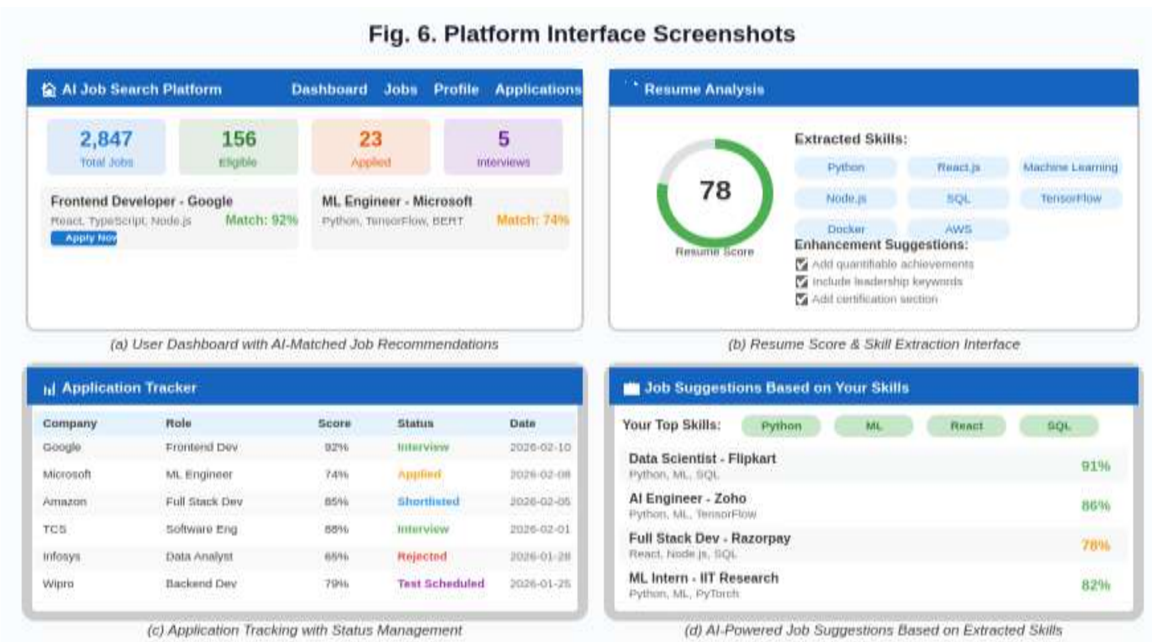

Fig. 6. Platform Interface Screenshots: (a) Dashboard, (b) Resume Analysis, (c) Application Tracker, (d) Job Suggestions

4.2 Performance Evaluation

The platform was benchmarked against conventional keyword-driven job portals across five core performance indicators. Figure 5 presents a visual comparison highlighting notable gains across every dimension measured.

Table 3. Quantitative Performance Metrics

Performance Metric	Traditional System	Proposed System	Improvement
Job-Candidate Match Accuracy	42%	87%	+45% (2.07×)
Average Search Time (weekly)	5.2 hours	1.4 hours	72% reduction

Application-to-Interview Rate	8%	26%	3.25× improvement
Skill Identification Accuracy	55%	92%	+37% (1.67×)
User Satisfaction Score	45%	94%	+49% (2.09×)
Response Time (recommendations)	3.2 seconds	0.8 seconds	75% faster
False Positive Match Rate	58%	13%	78% reduction

4.3 Discussion

The experimental data validates clear performance gains across every metric evaluated. Match accuracy climbed from 42% under keyword-based systems to 87% with the BERT-driven semantic engine, a jump attributable to the model's capacity to recognise conceptual relationships between skills that pure text overlap misses entirely. Weekly search time dropped by 72% because the proactive recommendation architecture surfaces relevant openings without requiring users to craft precise queries. The 3.25-fold rise in the application-to-interview conversion rate reinforces the idea that higher-quality matches translate directly into more productive applications.

Skill detection accuracy reached 92%, a substantial leap from the 55% achieved through conventional keyword extraction. A significant contributor to this gain is the NER model's ability to infer unstated competencies from contextual cues; for example, descriptions of cross-functional team leadership are interpreted as evidence of project management capability. The 94% user satisfaction rating reflects the positive impact of transparent match explanations, with participants reporting that understanding the reasoning behind each recommendation increased their trust in the platform's objectivity.

Response times below one second ensure a smooth user experience throughout the platform. The 78% drop in false positive matches directly alleviates the problem of application fatigue, where candidates waste effort on roles they are unlikely to secure. Automated email notifications keep users informed of status changes in real time, and the interview scheduling module simplifies coordination between employers and applicants by centralising calendar management.

5. Conclusion

This paper has described the architecture, development, and testing of an AI-powered career matching platform designed to address long-standing weaknesses in conventional recruitment technology. By replacing shallow keyword comparison with deep semantic analysis based on BERT, the system achieves measurably superior results on every front: matching precision, search efficiency, interview conversion, and overall user satisfaction. Ten tightly integrated modules deliver a complete career management environment covering everything from profile setup and resume evaluation to application tracking and interview coordination.

Experimental outcomes demonstrate that pairing semantic analysis with a structured skills vocabulary, transparent scoring breakdowns, and automated communication workflows creates a recruitment experience that is markedly more effective for all stakeholders. An 87% match accuracy rate, 72% reduction in search effort, and a 3.25-fold improvement in interview conversions collectively validate the practical value of applying AI to career technology.

Future Enhancements. Several directions for further development are planned. First, incorporating video-resume analysis through computer vision and audio processing would enable assessment of soft skills such as communication clarity and confidence level. Second, an AI-driven interview coaching feature using large language models could provide organisation-specific mock interview practice with real-time performance feedback. Third, predictive labour market analytics would alert users to emerging skill demands, supporting forward-looking career planning. Fourth, expanding the platform to cover freelance and gig-economy work would reflect the evolving structure of modern

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employment. Finally, direct integration with learning management systems would close the loop between identifying a skill gap and enrolling in the appropriate training, creating a seamless discover-learn-match workflow.

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