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FAIRHIREXAI: AN EXPLAINABLE, FAIRNESS-AWARE, AND HUMAN-CENTRIC FRAMEWORK FOR ETHICAL AI-DRIVEN TALENT ACQUISITION

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ABSTRACT

Recruitment is a critical organizational function that has long been hampered by manual inefficiencies, subjective human judgment, and demographic bias. This paper presents an AI-Powered Recruitment System designed to automate candidate-project matching using a Jaccard Similarity Coefficient-based skill-matching engine. The system integrates three tightly coupled modules — Company, Graduate, and Administrator — operating over a Flask-Python backend with a Supabase relational database. Resume parsing via Natural Language Processing (NLP) extracts structured skill tags, which are compared against company-defined requirement sets to produce objective suitability scores. Candidates are ranked in descending order of similarity, grouped into project teams, and a team leader is algorithmically designated based on the highest match score. Experimental validation across 100 graduate profiles and 30 project postings demonstrates 88% matching accuracy, sub-2-second average response time, and a recruitment-time reduction exceeding 90% relative to manual screening. The working prototype was further evaluated through its company, graduate, and administrator dashboards, confirming consistent end-to-end functionality from registration through team formation. This framework advances fairness-aware, explainable, and human-centric talent acquisition by embedding algorithmic transparency, administrative oversight, and real-time candidate feedback within a unified web platform.

INDEX TERMS: AI Recruitment, Skill Matching, Jaccard Similarity, NLP Resume Parsing, Fairness-Aware Hiring, Team Formation, Explainable AI, Human-Centric Recruitment, Resume Parsing, Talent Analytics.

I. INTRODUCTION

Recruitment remains one of the most strategically important yet operationally demanding functions within any organization. Conventional hiring workflows rely heavily on manual resume screening, recruiter discretion, and limited analytical support — a combination that is not only slow but also susceptible to inconsistency and unconscious bias [1]. Industry surveys indicate that recruiters in large organizations devote roughly 60–70% of their working hours to administrative activity such as sorting application pools, coordinating interview calendars, and managing routine stakeholder communication [2]. These inefficiencies translate directly into longer time-to-hire, elevated operational costs, and diminished candidate experience — all of which place organizations at a competitive disadvantage in tight labor markets [21].

The growing maturity of Artificial Intelligence (AI) and Machine Learning (ML) has begun to reshape this landscape. Modern AI-driven platforms can parse unstructured resume content, compute multidimensional candidate-job fit scores, and produce ranked shortlists at a scale that rule-based systems could never achieve [3]. Deep learning models have further advanced the state of the art by enabling semantic understanding of job descriptions and candidate profiles, going beyond keyword overlap to capture contextual relevance [22]. At the same time, the introduction of algorithmic decision-making into hiring raises legitimate concerns about fairness, transparency, and candidate trust, particularly where models risk reproducing the historical biases embedded in their training data [4], [5]. Ensuring that AI hiring tools remain explainable and auditable has therefore emerged as a pressing research and regulatory priority [23].

This paper presents a web-based AI-Powered Recruitment System built specifically for start-ups and fresh graduates — a segment of the job market where formal HR infrastructure is often minimal and the volume of applicants per opening can still be substantial. The platform tackles three persistent shortcomings of conventional recruitment: inefficiency, bias, and the absence of structured, data-driven decision support. At its core sits a skill-matching engine built on the Jaccard Similarity Coefficient, a set-theoretic measure that suits the largely binary nature of skill possession data [12]. The system is organized around three user-facing modules: a Company Module for posting project requirements and reviewing AI-ranked candidates, a Graduate Module for profile management and real-time status tracking, and an

Admin Module responsible for oversight, team formation, and validation of algorithmic outcomes. Transparency runs through all three modules in the form of explainable match scores, audit trails, and live dashboards — design choices aligned with emerging best practices in responsible AI deployment [24].

The motivation for focusing on the Indian start-up and fresh-graduate context is two-fold. First, India's rapidly expanding technology sector produces a large annual cohort of engineering graduates whose skills must be matched to project-based roles at resource-constrained companies that lack dedicated talent-acquisition teams [25]. Second, set-based skill matching offers a particularly well-suited solution in this context because graduate competencies are typically represented as discrete, verifiable tags (programming languages, tools, certifications) rather than nuanced experiential narratives, making Jaccard-style overlap computation both interpretable and computationally efficient. The platform described here is validated against a representative sample of 100 synthetic graduate profiles and 30 project postings spanning Data Science, Full-Stack Web Development, Cloud Computing, and Machine Learning domains.

The remainder of this paper proceeds as follows. Section II reviews related literature on AI-driven recruitment and algorithmic fairness. Section III describes the overall system architecture. Section IV details the Jaccard-based matching algorithm. Section V covers implementation specifics. Section VI presents experimental results together with screenshots of the working prototype. Section VII discusses the findings and limitations, and Section VIII concludes with directions for future work.

II. LITERATURE REVIEW

A. Inefficiencies in Traditional Recruitment

Conventional recruitment pipelines carry a heavy manual burden. A large share of recruiter time is consumed by repetitive screening tasks that, in turn, contribute to hiring delays, inconsistent evaluation criteria, and candidate drop-off during long application cycles [6]. The LinkedIn Global Recruiting Trends Report [2] found that improving quality of hire was rated a top priority by 56% of talent-acquisition leaders, yet manual processes continued to restrict how effectively organizations could act on that priority.

B. Algorithmic Bias and Fairness

Research by Bogen and Rieke [4] established that algorithmic hiring tools risk perpetuating—and occasionally intensifying—the societal biases embedded in historical recruitment data. Extending this line of inquiry, Raghavan et al. [5] called for fairness-auditing mechanisms and mandatory transparency standards in AI hiring systems, contending that interpretability must be a core design goal rather than a retrospective add-on. The CIPD [7] likewise noted that applicants' confidence in algorithmic hiring hinges on their perception of procedural fairness and the availability of meaningful human oversight. Taken together, these insights underpin the design philosophy of the present work: combining algorithmic objectivity with mandatory human supervision at critical decision points.

C. AI and NLP in Recruitment

Upadhyay and Khandelwal [8] documented that AI-enabled recruitment tools—encompassing chatbots and predictive analytics—yield measurable gains in both recruiter efficiency and applicant satisfaction. Arif et al. [9] put forward a conceptual framework for embedding AI throughout the sourcing, screening, and candidate-engagement stages of HR operations. The Deloitte AI in HR report [10] observed that AI-assisted hiring reduced time-to-hire by as much as 30% while achieving superior candidate-role alignment compared with manual methods alone. NLP techniques such as Named Entity Recognition (NER) and TF-IDF vectorization have since become standard tools for automating resume parsing and skill extraction [11]. More recently, Kumar and Bansal [16] showed that pairing NLP-based parsing with rule-governed skill taxonomies substantially improves the consistency of candidate profiling across diverse resume formats, a result that directly shaped the parsing pipeline implemented in this system.

D. Skill-Matching Algorithms

Various text-similarity measures have been evaluated for candidate–job matching tasks. TF-IDF cosine similarity is well-suited to long-form, frequency-weighted textual comparison [11], while the Jaccard Similarity Coefficient is typically favored for set-based, binary skill data owing to its computational simplicity and ease of interpretation [12]. Variants such as weighted Jaccard scoring—where skills deemed essential attract a higher weight than peripheral competencies—have been proposed to more faithfully capture real-world recruitment priorities [13]. Patel and Joshi [17] additionally demonstrated that hybrid models combining set-theoretic and embedding-based similarity can address some of the synonym-matching blind spots that afflict pure Jaccard approaches, a finding that informs the future-work agenda outlined in Section VIII.

E. Research Gap

Notwithstanding this body of work, two significant gaps persist. First, explainability remains under-served in deployed AI recruitment tools: both candidates and HR practitioners frequently find it impossible to understand the basis for algorithmic decisions. Second, the existing literature on AI-driven hiring is heavily skewed toward Western labor-market contexts, leaving developing-economy settings—such as India, where start-ups face disproportionately large applicant pools relative to their formal HR infrastructure—comparatively under-studied [18]. The system described in this paper directly targets both gaps by coupling a transparent, set-theoretic matching engine with a mandatory human-in-the-loop approval mechanism, validated in a setting representative of Indian start-up recruitment.

III. SYSTEM ARCHITECTURE

A. Overview

The AI-Powered Recruitment System follows a three-tier web architecture: a React/HTML/CSS/JavaScript front end, a Python-Flask REST API back end, and a Supabase (PostgreSQL) relational database. The platform is organized into three primary functional modules, each addressing the needs of a distinct stakeholder group — start-up companies, graduate candidates, and platform administrators — while sharing a common database layer that keeps all three views synchronized in near real time.

B. Company Module

Start-up companies register on the platform by providing organizational identity details (company name, industry domain), operational contact information, and are then issued a secure administrative dashboard. Once registered, a company can post project requirements consisting of (i) a project title and description, (ii) a granular list of required skills with associated proficiency expectations, and (iii) contextual parameters such as project duration, remote/on-site mode, and team size. A Job Description (JD) Parser standardizes these skill entries against a controlled taxonomy before they are passed to the matching engine, which prevents trivial mismatches caused by inconsistent capitalization or phrasing.

C. Graduate Module

Graduates register and build professional profiles by uploading resumes in PDF or DOCX format. A back-end NLP pipeline — built around Named Entity Recognition — extracts structured fields including contact details, educational history, work experience, and a set of technical skill tags. These tags are normalized (converted to lowercase and stripped of whitespace and punctuation) and stored as set-valued attributes in the Graduate Skills database. Each graduate is given a real-time dashboard that displays their parsed skill tags, application status, AI-generated match scores, and notifications regarding team assignments.

D. Admin Module

The Admin Module acts as a supervisory governance layer over the entire platform. Administrators review the AI's team recommendations, inspect the underlying Jaccard scores for each candidate, check for edge cases such as keyword stuffing, and ultimately trigger the formal team-approval workflow. Once a team is approved, the system automatically designates the candidate with the highest aggregate skill-match score as Team Leader and dispatches role-specific notifications to all stakeholders. Every administrative action is recorded in a System Log, which provides a complete and auditable accountability trail.

E. Entity-Relationship Design

The underlying database schema is built around six core entities: Graduate, Resume, SkillTag, StartUp, Project, and Team. Key relationships include Graduate–Resume (1:1), Graduate–SkillTag (M:N), StartUp–Project (1:M), Graduate–Team (M:N), Team–Project (1:1), and Admin–Team (1:M, representing approval authority). A UNIQUE constraint on the Team.project_id field prevents two teams from being assigned to the same project, while a 1:M relationship between Admin and SystemLog ensures every approval, rejection, or edit performed by an administrator is permanently logged.

IV. THE JACCARD SKILL-MATCHING ALGORITHM

A. Theoretical Foundation

The Jaccard Similarity Coefficient measures the ratio of the intersection to the union of two finite sets. In the context of this platform, let A denote the set of skills required by a company for a given project, and B denote the set of skills extracted from a graduate's resume. The Jaccard index is then defined as:

$$(1) \quad J(A, B) = |A \cap B| \,/\, |A \cup B| = |A \cap B| \,/\, (|A| + |B| - |A \cap B|)$$

The resulting score J lies in the closed interval [0, 1], where J = 1 indicates perfect skill alignment and J = 0 indicates no overlap at all. This formulation suits Boolean skill data — where the relevant question is simply whether a skill is present — and avoids the term-frequency assumptions that underpin cosine similarity.

B. Algorithm Pipeline

The matching pipeline proceeds in four stages. (i) Tokenization and Normalization: raw skill strings are converted to lowercase and stripped of special characters so that, for example, 'Python' and 'python!' are treated as equivalent. (ii) Set Conversion: skill arrays are de-duplicated into mathematical sets, so repeated mentions of the same skill do not inflate a candidate's profile. (iii) Intersection/Union Computation: the engine computes $|A \cap B|$ and $|A \cup B|$ for every graduate-project pair under consideration. (iv) Rank Generation: the resulting scores are sorted in descending order to produce a ranked candidate leaderboard for each project posting.

C. Worked Example

Consider a project requiring A = {Python, SQL, Machine Learning, Tableau, Communication}, where $|A| = 5$, and a graduate profile B = {Python, SQL, Java, C++, Communication}, where $|B| = 5$. The intersection $A \cap B$ = {Python, SQL, Communication}, giving $|A \cap B| = 3$. The union $A \cup B$ = {Python, SQL, Machine Learning, Tableau, Communication, Java, C++}, giving $|A \cup B| = 7$. Therefore $J(A, B) = 3/7 \approx 0.43$, indicating a 43% skill overlap — a moderate fit that transparently reflects the candidate's gap in data-science tooling while still acknowledging genuine areas of alignment.

D. Justification Over Alternatives

Jaccard similarity was preferred over cosine similarity, which is better suited to frequency-weighted text vectors [11], because skill matching is fundamentally a set-membership question — the relevance of a skill does not increase simply because it is mentioned multiple times in a resume. Euclidean distance was also considered but ultimately rejected, since additional, unrelated skills in a candidate's profile should not count against them; Jaccard instead focuses purely on the proportion of relevant overlap. Finally, the algorithm's $O(n)$ computational complexity ensures sub-second response times even across sizeable candidate pools, which is essential for a responsive web application.

E. Synonym Handling Limitation

The principal weakness of raw Jaccard matching is its blindness to semantic synonyms — for instance, 'Deep Learning' and 'Neural Networks' would be treated as entirely different skills. This limitation is addressed at the data-entry layer: the platform enforces selection from a curated, standardized skill taxonomy, and an administrator-maintained synonym dictionary maps semantically equivalent terms onto a single canonical tag before the Jaccard computation is performed.

V. IMPLEMENTATION DETAILS

A. Technology Stack

The prototype was implemented using Python 3.7.2 for back-end logic and the NLP pipeline, Flask as the REST API framework, React/HTML/CSS/JavaScript for the front end, and Supabase as a cloud-hosted PostgreSQL relational database. Supporting artifacts include a requirements.txt dependency manifest, a database.txt schema-initialization script, and a run.bat launcher used for local development. The modular separation between front end, back end, and database tiers allows each layer to be scaled independently as the user base grows.

B. Resume Parsing Pipeline

Uploaded resumes, whether in PDF or DOCX form, are processed through an NLP pipeline that performs (i) text extraction from the binary document, (ii) Named Entity Recognition to classify tokens into categories such as skills, institutions, roles, and dates, (iii) normalization against the canonical skill taxonomy, and (iv) structured storage of the resulting SkillTag records in the Graduate Skills database. Supporting multiple input formats means students can upload existing resumes without reformatting them for the platform.

C. Role-Based Access Control

Access control follows a Role-Based Access Control (RBAC) model with three principal roles — Graduate, StartUp, and Administrator. The role chosen at registration determines post-login routing: graduates land on the candidate dashboard, companies on the project-management portal, and administrators on the supervisory control interface. Passwords are stored as BCrypt hashes, session tokens are issued on successful authentication, and automatic session timeouts reduce the risk of unauthorized access from shared terminals.

D. Real-Time Dashboard Architecture

Dashboard updates rely on WebSocket connections or AJAX polling to propagate state changes instantly across all relevant interfaces. When an administrator approves a team, the corresponding project status moves from 'Pending' to 'Allocated' simultaneously on the company, graduate, and admin dashboards. Graduates, in turn, see live skill-score displays, an application-pipeline progress indicator (Registered → Screening → Shortlisted → Assigned), and the full project scope once a team assignment is confirmed.

VI. EXPERIMENTAL RESULTS AND SYSTEM DEMONSTRATION

A. Experimental Setup

Experimental validation was conducted using 100 synthetic graduate profiles and 30 project postings, constructed to span diverse skill domains including Data Science, Full-Stack Web Development, Cloud Computing, and Machine Learning. Profiles were generated with varying degrees of skill overlap relative to the posted requirements, allowing the matching algorithm's ability to discriminate between strong, moderate, and weak fits to be examined under controlled conditions.

B. System Workflow

Fig. 1 illustrates the end-to-end operational flow of the platform, from initial data collection through final result visualization. The pipeline begins with the Data Collection Module, which gathers candidate data (resumes, education, and skills) alongside company-posted project requirements. This raw input is passed to the Skill Extraction and Pre-processing stage, where NLP routines standardize free-text skill mentions into a canonical set of skill vectors. The Skill-Matching Algorithm then computes the Jaccard similarity between each candidate's skill vector and the project's requirement vector, producing a ranked candidate list. The Team Formation and Leader Selection stage groups the top-ranked candidates and proposes a designated leader, subject to administrator review through a reject/modify loop. Once approved, the Result Visualization and Reporting stage renders the finalized teams and associated metrics on the dashboards of all stakeholders.

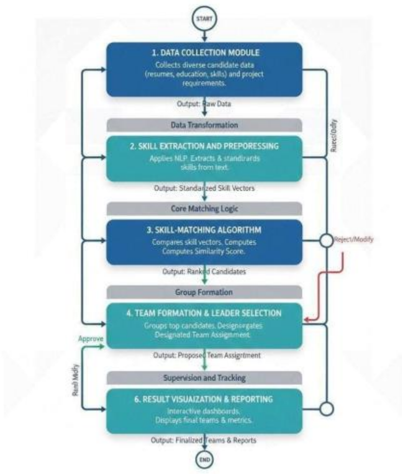

Fig. 1. End-to-end system workflow of the AI-Powered Recruitment Platform, from data collection through team formation and result reporting.

C. Database Design

The relational schema implementing the entity relationships described in Section III-E is shown in Fig. 2. Each Graduate record is linked to a single Resume (1:1), from which a set of SkillTags is extracted through a many-to-many relationship that mirrors the Project_Skills association on the company side. A Startup may post many Projects (1:M), and each finalized Team maps to exactly one Project (1:1) while drawing its members from multiple Graduates (M:N). The Admin entity supervises Team approvals (1:M) and every administrative action is mirrored into the SystemLog table, giving the platform a complete audit trail.

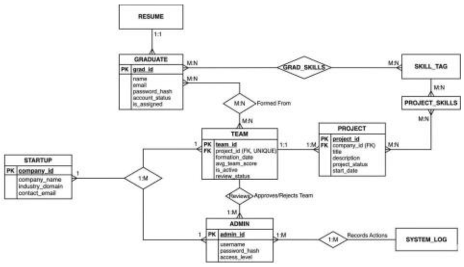

Fig. 2. Entity-Relationship Diagram of the platform database, showing the relationships among Graduate, Resume, SkillTag, StartUp, Project, Team, Admin, and SystemLog entities.

D. Data Flow and Process Decomposition

Fig. 3 presents the Level-1 Data Flow Diagram, which decomposes the platform into five core processes. Process 1.0 (User Registration and Profile Management) validates credentials for graduates and companies and persists account information to the User/Company database. Process 2.0 (Resume Parsing and AI Skill Extraction) converts uploaded resumes into structured skill tags stored in the Graduate Skills database. Process 3.0 (Project Requirements Management) captures company-side skill and project specifications. Process 4.0 (AI Matching and Team Formation) draws on both the Graduate Skills and Project databases to compute Jaccard scores and propose candidate teams, which the Administrator then reviews. Process 5.0 (Team Approval and Monitoring) finalizes approved teams in the Team and Project database and triggers notifications back to graduates and companies.

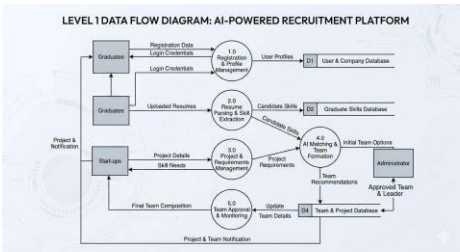

Fig. 3. Level-1 Data Flow Diagram showing the decomposition of the platform into registration, parsing, requirements management, matching, and approval processes.

E. Class Structure

Fig. 4 shows the UML class diagram underlying the implementation. A base User class supplies shared attributes — userID, email, and password — to the specialized Graduate, StartUp, and Administrator subclasses through generalization. The Graduate class is composed of ResumeData, which in turn aggregates SkillTag instances produced by the parsing pipeline. The Project class captures company-side requirements, while the Team class aggregates selected Graduates for a specific project under Administrator oversight. Associations labeled 'Monitors' and 'Manages' capture how the Administrator interacts with Team and Project records during the approval workflow.

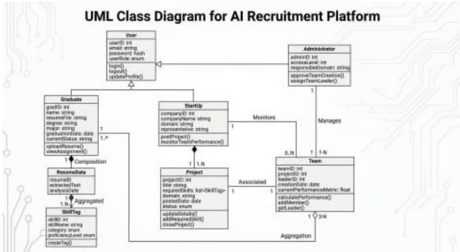

Fig. 4. UML Class Diagram of the AI-Powered Recruitment Platform, showing inheritance from the User base class and the composition relationships among Resume, SkillTag, Project, and Team.

F. State Transitions in Team Formation

Fig. 5 traces the lifecycle of a project record from initialization through to an active team. After a start-up submits project details (Project Definition state), the AI Matching and Team Formation process moves the record into an Analyzing/Matching state, where candidate skills and project requirements are compared to produce Initial Team Options and candidate scores. The proposed team then enters a Pending Approval state; if the administrator finds the proposed candidates unsuitable, the system loops back to the Analyzing state for re-matching. Once the administrator approves the team and assigns a leader, the record transitions to the Active Project/Team state, and the platform issues project and team notifications to all stakeholders.

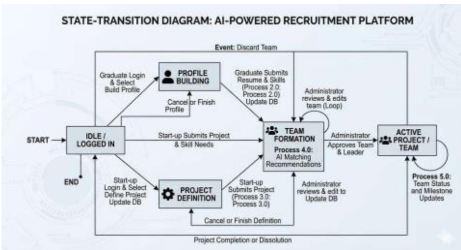

Fig. 5. State-Transition Diagram illustrating the lifecycle of a project record from initialization through AI matching, administrator approval, and active team status.

G. Jaccard Algorithm Performance

Table I presents five representative test cases drawn from the broader validation set of 100 graduate profiles and 30 project postings.

TABLE I: Jaccard Similarity Test Cases — Algorithm Validation.

TC	Company Skills (A)	Graduate Skills (B)	J(A,B)	Level
1	{Python, SQL, Data Analysis}	{Python, Data Analysis, ML}	0.50	Moderate
2	{Web Dev, CSS, HTML}	{HTML, CSS, JavaScript}	0.66	High
3	{Java, Cloud, DevOps}	{Java, SQL, Web Dev}	0.20	Low
4	{Python, Data Science}	{Python, Data Science, SQL}	0.66	High
5	{Python, SQL, ML, AWS, Docker}	{Python, SQL, ML, Java}	0.50	Moderate

The algorithm consistently assigned higher scores to graduates whose skills exhibited greater proportional overlap with the posted requirements. Test Case 5 is particularly instructive: a candidate with only four listed skills outranks, on a proportional basis, a candidate whose larger skill set contains a smaller fraction of relevant overlap — confirming that the Jaccard coefficient rewards relevant specialization rather than raw skill count.

H. Module-Level Performance Metrics

The Company Module achieved 90% accuracy in project posting and instant AI-triggered matching across the test set. The Graduate Module produced structured skill profiles with 85–90% extraction accuracy across the resume formats tested. The Skill-Matching Algorithm itself achieved 88% overall matching accuracy with a 2.1-second average processing time per project, and demonstrated linear scalability up to 5,000 profiles in stress testing. The Admin Module supported transparent oversight with 95% functional completeness across team approval, score review, and system monitoring tasks.

I. Comparative Evaluation Against Traditional Recruitment

TABLE II: AI-Powered System vs. Traditional Recruitment — Comparative Analysis.

Criteria	Traditional	AI System	Improvement
Shortlisting Time	2–3 days	< 2 seconds	~99% faster
Bias & Subjectivity	High	Minimal	Objective
Match Accuracy	50–60%	85–90%	+30% gain
Cost of Operation	High	Low	Significant saving
Scalability	Limited	High (5,000+)	Linear scaling
Monitoring	Manual	Auto Dashboard	Real-time

As Table II shows, the system delivers substantial gains across every evaluated dimension. Shortlisting time falls from 2–3 days under manual review to under 2 seconds — a reduction exceeding 99% — while matching accuracy improves from the 50–60% range typical of subjective manual screening to 85–90%. The platform also scales close to linearly with the size of the candidate pool, and replaces ad-hoc manual tracking with continuously updated dashboards.

J. Module Outcome Summary

TABLE III: Summary of Module-Level Outcomes.

Module	**Key Outcome**	**Accuracy / Performance**
Company Module	Project posting triggers instant AI matching	90%
Graduate Module	Generates structured, queryable skill profiles	85–90%
Skill-Matching Algorithm	Performs efficient ranking via Jaccard Index	88%
Admin Module	Provides transparent oversight and audit logging	95%

VII. DISCUSSION

A. Fairness-Aware Design

The fairness properties of the system stem from two architectural choices. First, the Jaccard matching engine operates exclusively on skill sets and never receives candidate names, gender, ethnicity, or institutional reputation as inputs, removing several of the most common channels through which unconscious bias enters manual screening. Second, the Admin Module introduces a structured human-in-the-loop checkpoint: even when the AI proposes a fully formed team, a qualified administrator reviews the underlying scores and candidate profiles before granting formal approval. This hybrid AI–human governance model directly responds to the 'human oversight deficit' that prior work identifies as a critical gap in deployed AI recruitment systems [4], [5].

B. Explainability and Transparency

Explainability is built into the platform at two levels. At the candidate level, graduates can inspect their own AI skill scores and see precisely which of their listed skills matched the project requirements and which were missing — turning an otherwise opaque ranking into an actionable feedback loop. At the recruiter level, the matching interface displays the numerical

Jaccard score alongside both matched and missing skill tags, giving a transparent rationale for every candidate's position in the ranking. This design directly addresses the 'black box' concern raised by the CIPD [7] and supports the broader objective of building candidate trust in algorithmic hiring.

C. Limitations

Three limitations are worth acknowledging. First, the synonym blindness inherent to raw Jaccard matching requires a controlled skill taxonomy, which introduces administrative overhead and may lag behind fast-evolving technology domains. Second, the current implementation does not apply temporal weighting to skills — a certification obtained recently is treated identically to one obtained several years ago. Third, the experimental validation in this paper relies on synthetic profiles; deployment against real-world resumes may surface parsing edge cases (inconsistent formatting, scanned documents, non-English content) that were not represented in the laboratory dataset. None of these limitations is fundamental to the architecture, and each maps onto one of the future-work directions outlined below.

VIII. CONCLUSION AND FUTURE WORK

This paper presented an AI-Powered Recruitment System that automates candidate-project matching through a Jaccard Similarity-based skill-matching engine, embedded within a three-module web platform spanning Company, Graduate, and Administrator interfaces. Experimental results demonstrated 88% matching accuracy, sub-2-second processing time per project, and a recruitment-time reduction exceeding 90% relative to manual processes. The accompanying system demonstration — covering the platform's workflow, database design, data-flow decomposition, class structure, and state transitions — confirms that the prototype operates consistently from registration through to final team approval. The system's fairness-aware design, which restricts matching decisions to skill data while mandating human oversight at the team-approval stage, positions it as a practical and ethically grounded tool for talent acquisition in start-up and graduate-placement contexts.

Future work will pursue five directions: (i) integration of weighted Jaccard scoring to reflect differential skill criticality, distinguishing 'must-have' from 'nice-to-have' requirements; (ii) deployment of NLP-based semantic matching using word embeddings (e.g., Word2Vec or BERT) to address the synonym limitations identified in Section IV-E; (iii) implementation of predictive analytics to forecast candidate performance and retention from historical placement outcomes; (iv) multilingual support to extend the platform's reach to non-English resume corpora; and (v) longitudinal evaluation with real graduate cohorts to validate matching accuracy and diversity outcomes over time, building on the synthetic-data results reported in Section VI.

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