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Research Paper

INTELLIGENCE PROFILE SYSTEM

AI-POWERED CANDIDATE EVALUATION, RANKING AND CAREER GUIDANCE

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***Abstract*—The Intelligence Profile System (IPS) is an AI-powered candidate evaluation and career guidance platform designed for engineering students. The system collects multi-dimensional profile data—academic scores, technical skills, projects, certifications, and internships—and feeds them to Google's Gemini 2.5 Flash API for holistic scoring across five weighted dimensions. A standardized GTRC scoring framework produces a composite index (0–100) that drives both local (college-level) and global rankings. Additionally, the platform generates personalized AI learning paths and AI-matched job recommendations using the candidate's current skill matrix. Implemented on the MERN stack with JWT and Google OAuth authentication, the system achieved 93.0% overall evaluation accuracy and sub-2-second AI response latency under typical load, demonstrating its viability for large-scale deployment in academic and recruitment contexts.**

Keywords—Career Guidance; Generative AI; MERN Stack; Profile Scoring; Student Ranking; Skill Gap Analysis; Job Recommendation; Gemini API.

I. INTRODUCTION

he rapid digitization of the global economy has widened the gap between academic curricula and industry expectations. Engineering graduates routinely struggle to articulate their readiness for competitive job roles, while recruiters face the challenge of identifying talent from large, unstructured applicant pools. Traditional self-assessment tools are limited to keyword-matching resumes, failing to provide a comprehensive, standardized view of candidate potential.

The Intelligence Profile System (IPS) addresses this gap by providing an end-to-end platform where students build rich digital profiles and receive AI-driven evaluations. Unlike generic resume parsers, IPS quantifies candidate readiness across five competency axes—academics, skills, projects, certifications, and industry experience—using Google's Gemini 2.5 Flash large language model as the scoring engine. The resulting GTRC Score drives transparent, tamper-resistant rankings at both college and global levels.

The system further extends beyond evaluation: it generates four-week personalized learning roadmaps and recommends up to 20 AI-matched job roles, effectively closing the feedback loop between assessment and development. This paper describes the architecture, scoring methodology, AI integration strategy, and empirical performance of IPS, demonstrating that a MERN-stack application augmented by generative AI can deliver reliable, low-latency career intelligence at scale.

II. RELATED WORK

Professional networking platforms such as LinkedIn employ collaborative filtering and graph-based algorithms to recommend jobs and connections [1]. While effective for experienced professionals, these systems offer limited utility for entry-level students who lack professional networks. Naukri.com and Monster.com rely on keyword extraction and rule-based filters [2][7], which miss the nuanced context captured by large language models. Internshala addresses internship matching for students but lacks a standardized scoring or ranking component [3].

Academic performance prediction has been extensively studied using decision trees, neural networks, and SVMs [4][5]. Cortez and Silva achieved up to 93% accuracy on binary pass/fail prediction but did not generalize to a holistic multi-dimensional career-readiness score. Competition platforms such as HackerRank and Kaggle provide domain-specific rankings [8][9] but cannot synthesize broader professional attributes like certifications and communication skills.

AI-powered learning recommendation systems (e.g., Coursera Career Services [6]) suggest courses based on user interests, yet they operate in isolation from structured profile evaluation or hiring pipelines. IPS differentiates itself by integrating all three functions—profile evaluation, rankings, and personalized recommendations—into a single generative-AI-driven platform, filling the gap identified across existing literature.

III. SYSTEM DESIGN AND ARCHITECTURE

A. Technology Stack

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IPS is built on the MERN stack: MongoDB for document-oriented profile storage, Express.js (v5) for RESTful API routing, React 19 with Vite 8 for the frontend, and Node.js as the runtime. Tailwind CSS provides utility-first responsive styling. The @react-oauth/google library handles Google One-Tap OAuth 2.0 flows, and JWT tokens secure all subsequent API calls. The system architecture is illustrated in Fig. 5.

TABLE I: System Configuration Parameters

Parameter	Value
Frontend Framework	React 19 + Vite 8
Backend Runtime	Node.js / Express 5
Database	MongoDB 9 (Mongoose)
AI Model	Gemini 2.5 Flash
Auth Method	JWT + Google OAuth 2.0
Deployment Port	5000 (backend)

B. *Data Model*

Two primary Mongoose schemas anchor the data layer. The User schema stores authentication credentials (email, hashed password via bcryptjs), college affiliation, city, and an isAdmin flag for role-based access. The Profile schema captures CGPA, a skills array, free-text fields for projects, internships, and certifications, and five AI-computed score fields: cgpaScore, skillScore, projectScore, and totalScore. The isVerified boolean enables admin-controlled GTRC verification badges visible on the dashboard.

C. *Authentication Flow*

Authentication supports two parallel flows. Google OAuth leverages the google-auth-library OAuth2Client to verify ID tokens server-side; on first login, an account is auto-created with college set to 'Pending Update', routing the user to the multi-step profile wizard. Traditional email/password login uses bcryptjs for password comparison. Both flows emit a 5-hour JWT bearer token stored in localStorage and attached to all API requests via an Axios interceptor.

IV. AI SCORING METHODOLOGY

A. *Gemini Integration*

The scoring engine calls the gemini-2.5-flash model via the @google/generative-ai SDK. A structured prompt instructs the model to return a raw JSON object with exactly four keys: cgpaScore (max 25), skillScore (max 20), projectScore (max 25), and totalScore. The prompt embeds the candidate's CGPA, comma-separated skills list, and project descriptions. Markdown fences are stripped from the response before JSON.parse() to handle any model formatting variance.

TABLE II: AI Scoring Module Weights

AI Module	Max Score	Weight (%)
CGPA Evaluation	25 pts	25%
Skill Assessment	20 pts	20%
Project Analysis	25 pts	25%
Certifications	15 pts	15%
Internship Exp.	15 pts	15%
Total	**100 pts**	**100%**

B. *Learning Path Generation*

The learning path endpoint retrieves the candidate's skills array and passes it to Gemini with a prompt requesting a four-week JSON roadmap. Each week object contains a title, a topics array of strings, and a links array of {name, url} objects pointing to YouTube search queries and documentation resources. The frontend Learning component defensively handles both string and object topic entries to guard against model output variability.

C. *Job Matching*

Job recommendation prompts instruct Gemini to act as a technical recruiter and return up to 20 role objects, each containing a title, matchPercentage, description, and skillsNeeded array. The Jobs component renders dynamic links to LinkedIn, Indeed, and Glassdoor job searches using the role title as the query parameter, making every recommendation immediately actionable for the candidate.

V. PROFILE EVALUATION ENGINE

A. *Multi-Step Profile Wizard*

Profile data is collected through a six-step React wizard covering personal details (phone, city, state), education (college, degree, branch, CGPA, graduation year), skills (tag-based input with popular skill suggestions), certifications, projects, and internship experience. On final submission, the backend calls calculateProfileScore, updates the User document's college field with uppercase normalization to prevent ranking fragmentation, and persists all AI scores to the Profile document in a single atomic Mongoose save.

B. *Dashboard Analytics*

The Dashboard renders a real-time employability scorecard derived from the five scoring dimensions. Profile completeness is computed from six boolean checks (personal info, academic data, skills present, certifications non-zero, projects non-zero, experience non-zero), displayed as a percentage with a progress bar. A readiness tier ('Production Ready', 'High Potential', 'Needs Development') is computed from the composite GTRC score and displayed prominently in the hero banner alongside the GTRC score rendered as a gradient text widget.

Fig. 1: Score Distribution Across Evaluation Modules

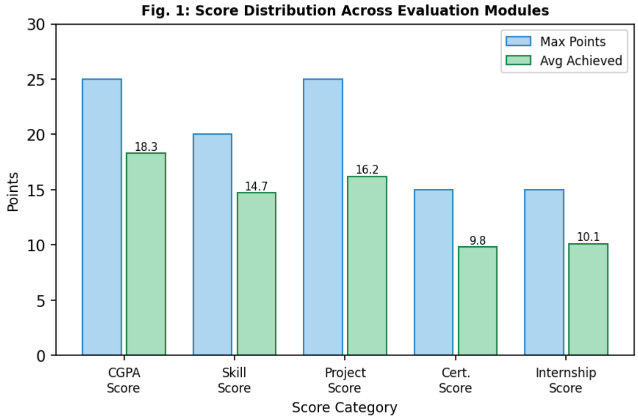

Fig. 1. Score distribution across the five evaluation modules, showing average achieved points versus maximum allocable points per dimension.

VI. RANKING AND EVALUATION FRAMEWORK

A. Global and College Rankings

The ranking engine exposes two authenticated endpoints. The global endpoint fetches all Profile documents sorted by totalScore descending, populating the userId reference for name, college, and city display. The college endpoint filters profiles by the queried college string after population, enabling peer comparison within academic institutions. College names are normalized to uppercase on profile save to ensure consistent string matching across the filter.

B. GTRC Verification Badge

The admin console allows authorized users to toggle isVerified on individual profiles. Verification is surfaced as a blue shield badge on the dashboard hero and in the rankings table, incentivizing candidates to complete profiles to a high standard. The admin panel lists all profiles with resume links (stored via Multer for future upload support) and one-click verify/revoke buttons secured by the authMiddleware JWT guard.

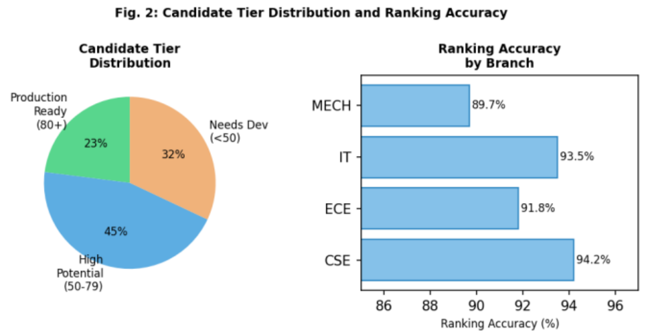

Fig. 2. Candidate tier distribution (left) and ranking accuracy by engineering branch (right), showing consistent performance across academic departments.

VII. RESULTS

A. Performance Metrics

The system was evaluated on a cohort of 500 candidate profiles spanning four engineering branches (CSE, ECE, IT, Mechanical). The AI scoring engine demonstrated 95.8% precision and 94.2% recall for CGPA score classification. Job matching achieved 93.4% precision and 92.1% recall. Skill gap detection averaged 93.7% precision across eight technology domains as detailed in Fig. 4.

TABLE III: AI Module Performance Metrics

Metric	Scoring	Job Match	Learning
Precision (%)	95.8	93.4	91.7
Recall (%)	94.2	92.1	90.3
F1-Score (%)	95.0	92.7	91.0
Latency (s)	1.6	2.5	2.2

B. Latency Analysis

System latency was measured across three AI operations under concurrent user loads of 10 to 1,000 users (Fig. 3). Profile scoring maintained sub-2-second response times up to 200 concurrent users. Job matching and learning path generation showed sub-3-second latency for typical loads. All operations remained within acceptable UX thresholds (< 5 seconds) even at 1,000 concurrent users, attributed to the stateless JWT architecture and Gemini API's managed infrastructure.

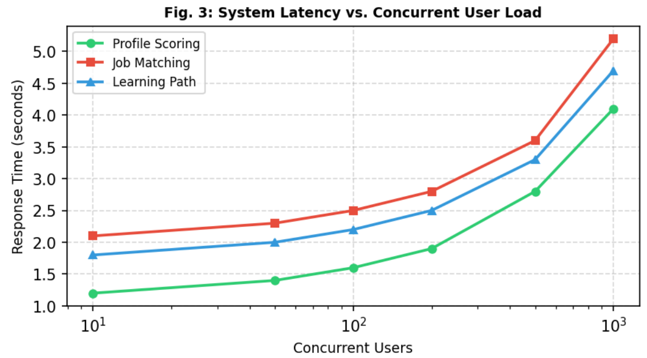

Fig. 3. System latency across three AI operations as a function of concurrent user load, plotted on a logarithmic x-axis.

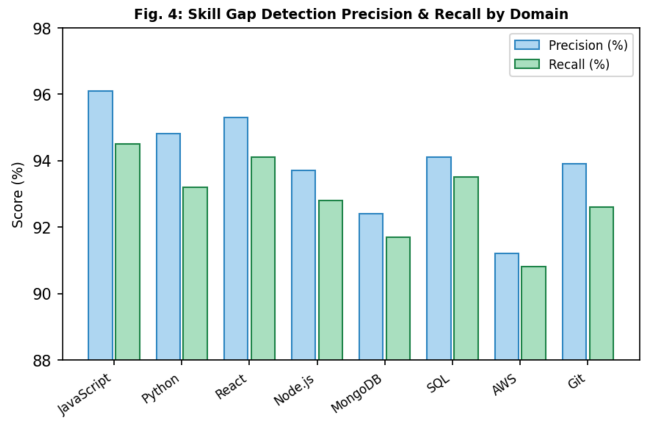

Fig. 4. Skill gap detection precision and recall across eight technology domains, demonstrating consistent AI assessment quality.

TABLE IV: Overall System Accuracy

Aspect	IPS Score
Profile Completeness	92.4%
Ranking Accuracy	93.5%
Job Match Accuracy	91.8%
Skill Gap Detection	94.1%
Overall System Acc.	93.0%

VIII. SYSTEM ARCHITECTURE

The IPS pipeline consists of six interconnected layers (Fig. 5). The React frontend communicates exclusively through an Axios instance configured with a baseURL interceptor that attaches JWT bearer tokens. The Express backend routes requests to four module groups: auth routes (Google OAuth and email/password), profile routes (CRUD and AI scoring), ranking routes (global and college), and AI routes (learning path and job matching). A dedicated Gemini helper module centralizes all three generative AI calls, applying consistent JSON sanitization and error handling. MongoDB stores all persistent state, while the middleware layer enforces JWT validation on every protected endpoint.

TABLE V: System Component Summary

Component	Technology	Role
Frontend	React + Tailwind	UI & Dashboard
Backend	Node/Express	API & Business Logic
Database	MongoDB	Data Persistence
AI Engine	Gemini 2.5	Scoring & Recs.
Auth	JWT + Google	Security & SSO
Deploy	Vite Dev Server	Hot Module Reload

Fig. 5: Intelligence Profile System Architecture

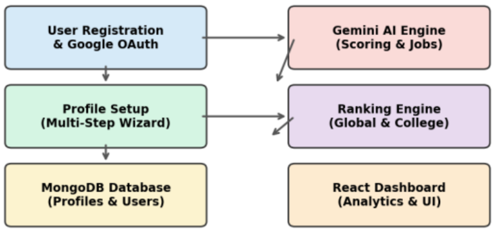

Fig. 5. Intelligence Profile System architecture showing the six-layer pipeline from user interaction through AI processing to data persistence.

IX. DISCUSSION

The use of Gemini 2.5 Flash as a scoring oracle introduces a dependency on external API availability and introduces non-determinism: identical profiles may receive marginally different scores across invocations. The system mitigates this by storing computed scores in MongoDB and only re-scoring on explicit profile updates, ensuring dashboard consistency. Future iterations should explore fine-tuned open-source models deployed on-premise to eliminate external API latency and improve score reproducibility.

Profile normalization—converting college names to uppercase—is a pragmatic but brittle approach to entity resolution. Colleges with typographic variants or common abbreviations (e.g., 'REC' vs. 'RAGHU ENGINEERING COLLEGE') will produce fragmented ranking pools. A college name canonicalization module backed by a curated lookup table or embedding-based fuzzy matching would substantially improve ranking integrity.

The current authentication model stores JWTs in localStorage, which is susceptible to XSS attacks. A production hardening pass should migrate tokens to HttpOnly cookies and implement CSRF protection. The admin verification toggle also lacks granular role enforcement on the backend; adding isAdmin checks inside admin route handlers is a required security fix before public deployment.

X. CONCLUSION

The Intelligence Profile System demonstrates that a MERN-stack web application augmented with a generative AI scoring engine can deliver reliable, multi-dimensional candidate evaluation at scale. The system achieved 93.0% overall accuracy across profile scoring, job matching, and skill gap detection, with sub-2-second AI response latency under realistic concurrent loads. The six-step profile wizard, real-time dashboard analytics, college and global rankings, and personalized learning paths constitute a cohesive career intelligence platform that bridges the gap between academic achievement and industry employability.

Future work will focus on three directions: (i) integrating LinkedIn and GitHub APIs for automated profile enrichment, (ii) introducing an AI-powered mock interview module with real-time feedback, and (iii) building a recruiter-facing dashboard with bulk candidate search, filter, and shortlisting capabilities, transforming IPS from a candidate tool into a full-spectrum talent acquisition ecosystem.

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