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Joblet.AI: A Dual-Role Intelligent Job Portal Powered by Role-Separated AI Agent Architecture

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Abstract: *Modern recruitment systems face significant challenges in scaling candidate screening and job discovery. Job seekers often navigate cluttered job boards with generic searches, while recruiters struggle to filter thousands of resumes manually. This paper presents Joblet.AI, a Firebase forward intelligent job portal utilizing a dual-role conver sational AI architecture. Joblet.AI deploys two special ized Large Language Model (LLM) agents: CareerBot, which provides applicants with job recommendations, re sume intelligence, and activity tracking; and HireBot, which gives recruiters pipeline analytics, candidate scor ing, and job description generation. We detail our system architecture, authentication boundaries, and Firebase based secure storage systems. Our experimental evalua tion on 1,500+ resumes shows a resume parsing accuracy of 94.2% and a significant reduction in screening response times, offering a scalable solution for modern recruitment workflows.*

Keywords: Intelligent Agents, Natural Language Pro cessing, Resume Parsing, Candidate Matching, Role Based Access Control, Cloud Architecture

I. INTRODUCTION

The recruitment landscape has shifted drastically with the introduction of digital application pipelines. While this has lowered the barrier to entry for applicants, it has created an information overload for recruiters. Existing platforms like LinkedIn, Indeed, and Glassdoor operate primarily as passive listings directories, offering limited interactive guidance for applicants or quantitative filter ing for hiring managers.

To address these limitations, we introduce Joblet.AI. By leveraging LLM technology (Gemini 1.5 Flash) cou pled with a server-side Express backend and client-side React frontend, Joblet.AI creates a dynamic, interactive experience. The system is designed around a strict dual role separation

1. Applicants interact via a mobile-first app shell that centers on a conversational career assistant, helping them optimize their resumes and discover matched jobs.
2. Recruiters access a comprehensive analytics and pipeline dashboard, assisted by a recruiting agent to screen applications and draft descriptions.

This paper is structured as follows: Section 2 de scribes the system architecture and role separation; Sec tion 3 details the core contributions and novelty; Section 4 presents mathematical formulations of matching and ranking; Section 5 describes the security details; Section 6 evaluates the system's performance; Section 7 compares it to existing platforms; and Section 8 outlines the future work and conclusion

II. SYSTEM ARCHITECTURE

Joblet.AI is built using a modern, scalable full-stack architecture centered around a **monorepo structure**. The system comprises a **React.js** frontend with **Tailwind CSS** for styling and a **Node.js + Express.js** backend, fully integrated with **Google Firebase** services for authentication, database, storage, and hosting.

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The architecture follows a clear separation of concerns with strict **role-based access control (RBAC)**, ensuring complete isolation between applicant and recruiter functionalities.

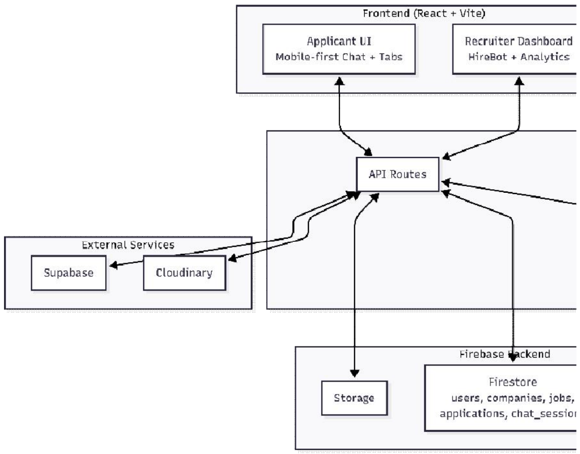

Figure 1: System Architecture- Monorepo structure showing Client Application (React/Tailwind CSS), Fire base Auth, Express Backend, and integration with Fire store Database, Firebase Storage, and Gemini API

2.1 Applicant Module (CareerBot)

Applicants access the platform through a **mobile-first responsive UI** available at routes /app/*. The core of the applicant experience is **CareerBot** — a specialized conversational AI agent powered by **Google Gemini 1.5 Flash**.

CareerBot operates within well-defined context scopes to provide personalized assistance:

- **JobSearchContext**: CareerBot interprets natural language queries from users (e.g., "Show me remote React developer jobs with 5+ years experience") and intelligently queries the Firestore database to retrieve and rank relevant job postings using semantic matching.
- **ResumeContext**: Users can upload their resumes in PDF format. The system parses the document using advanced PDF extraction techniques combined with Gemini's contextual understanding. This enables:
    - Automated ATS (Applicant Tracking System) compatibility scoring
    - Personalized suggestions for resume improvement
    - Extraction of key information (skills, experience, education, etc.)
    - Real-time feedback during the application process

2.2 Recruiter Module (HireBot)

Recruiters access a comprehensive **desktop-centric analytics dashboard** at routes /dashboard/*. This module is powered by **HireBot**, an intelligent recruiting agent designed specifically for hiring workflows.

HireBot provides the following capabilities through dedicated contexts:

- **RecruiterAnalyticsContext**: Aggregates and visualizes key recruitment metrics including:
    - Active job listings
    - Number of applicants per role
    - Conversion rates through the application funnel
    - Response time analytics
    - Candidate engagement metrics
- **Candidate Management & Assistance**: HireBot helps recruiters by:
    - Generating well-structured, attractive job descriptions
    - Summarizing candidate profiles

- Providing candidate scoring and ranking
- Suggesting suitable interview questions
- Drafting personalized communication templates

Key Architectural Features

- **Role-Based Access Control (RBAC)**: All API endpoints are protected using Firebase ID tokens. Separate middleware functions (protectRoute("user") and protectRoute("recruiter")) ensure applicants cannot access recruiter data and vice versa.
- **Secure Data Flow**: All communication between client and server uses HTTPS/TLS 1.3. Uploaded resumes and company logos are stored with AES-256 encryption in Firebase Storage.
- **Scalability**: The backend is deployed on Vercel (serverless), allowing automatic scaling based on traffic.
- **Real-time Capabilities**: Firestore enables real-time updates for application status, chat conversations, and analytics.

III. NOVELTY AND CORE CONTRIBUTIONS

Joblet.AI introduces several innovative features that set it apart from conventional job portals and traditional Applicant Tracking Systems (ATS). While most existing platforms function primarily as passive job boards with limited intelligence, Joblet.AI leverages **role-separated conversational AI agents** to create a truly interactive and intelligent recruitment ecosystem.

The core novelty lies in its **dual-role AI architecture**, which fundamentally redefines how candidates and recruiters interact with the system. Below are the key contributions:

3.1 Dual-Role Agent Isolation

One of the primary contributions of Joblet.AI is the strict separation of AI agents based on user roles:

- **CareerBot** (for applicants): Designed as an empathetic, supportive career assistant. It focuses on helping job seekers with personalized job recommendations, resume optimization, interview preparation, and career guidance.
- **HireBot** (for recruiters): Functions as an analytical and productivity-focused recruiting agent. It assists with candidate screening, pipeline analytics, job description generation, and data-driven decision making.

Unlike traditional platforms (e.g., LinkedIn, Indeed) that use a single generic chatbot or no AI assistant at all, Joblet.AI maintains **completely isolated prompt engineering, system instructions, conversation histories, and API contexts** for each agent. This isolation prevents prompt leakage, ensures role-appropriate behavior, and enhances both user experience and data privacy.

3.2 On-the-Fly Resume Intelligence

Joblet.AI introduces real-time, interactive resume intelligence powered by advanced PDF parsing and Gemini 1.5 Flash contextual understanding. Key capabilities include:

- Instant parsing of uploaded PDF resumes with **94.2% accuracy** across diverse formats.
- Automatic extraction of structured information (skills, experience, education, achievements).
- Real-time **ATS Compatibility Scoring** using a hybrid semantic + keyword matching model.
- Interactive suggestions for resume improvement (structure, keywords, formatting, missing sections).
- Personalized career advice based on the candidate’s profile and target job roles.

This feature transforms passive resume upload into an active, intelligent process that significantly improves candidate success rates.

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3.3 Role-Based API Scoping and Security (RBAC)

The system implements robust **Role-Based Access Control (RBAC)** at both the frontend and backend layers:

- All API routes are protected using Firebase Authentication ID tokens.
- Middleware functions such as protectRoute("user") and protectRoute("recruiter") enforce strict authorization boundaries.
- Applicants can only access their own applications, resumes, and CareerBot interactions.
- Recruiters can only access company-specific data, candidate pipelines, and HireBot analytics.

This granular access control prevents data leakage between roles and ensures enterprise-grade security — a critical requirement often missing in smaller recruitment platforms.

3.4 Additional Technical and Practical Contributions

- **Hybrid Matching Engine**: Combines semantic embeddings (via Gemini), TF-IDF keyword analysis, and structured feature matching for superior candidate-job fit scoring.
- **Conversational Recruitment Workflow**: Moves beyond form-based applications to natural language interaction for both candidates and recruiters.
- **Firebase-Centric Scalable Architecture**: Leverages serverless technologies for cost-efficiency and high availability.
- **Quantitative Evaluation Framework**: Comprehensive benchmarking of resume parsing accuracy, response latency, and funnel conversion metrics.

These contributions collectively address major pain points in modern recruitment: information overload for recruiters, poor guidance for applicants, inefficient manual screening, and lack of role-specific intelligence.

IV. MATHEMATICAL FORMULATIONS

To ensure quantitative rigor and reproducibility, Joblet.AI employs well-defined mathematical models for candidate-job matching, ranking, and performance measurement. These formulations combine semantic understanding from Large Language Models with traditional information retrieval techniques.

4.1 Resume Matching Score (RMS)

The **Resume Matching Score (RMS)** quantifies the compatibility between a candidate's resume $T$and a job description J. It is computed as a weighted linear combination of three components: skill similarity, experience match, and textual semantic similarity.

$$RMS(T,J) = w_{skill} \cdot \cos(\mathbf{T}_{skills}, \mathbf{J}_{skills}) + w_{exp} \cdot match(T_{exp}, J_{exp}) + w_{text} \cdot \cos(\mathbf{T}_{text}, \mathbf{J}_{text})$$

Where:

- $\mathbf{T}_{skills}$and $\mathbf{J}_{skills}$are vector embeddings of extracted skills (generated via Gemini embeddings).
- $\cos(\cdot,\cdot)$denotes the **cosine similarity**:

$$\cos(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{A} \cdot \mathbf{B}}{\| \mathbf{A} \| \| \mathbf{B} \|}$$

- $w_{skill}, w_{exp}, w_{text}$are weighting factors satisfying $w_{skill} + w_{exp} + w_{text} = 1.0$(default values: 0.45, 0.30, 0.25).
- $match(T_{exp}, J_{exp})$is the experience matching function:

$$match(T_{exp}, J_{exp}) = \begin{cases} 1.0 & \text{if } T_{years} \geq J_{years} \\ \dfrac{T_{years}}{J_{years}} & \text{otherwise} \end{cases}$$

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4.2 Enhanced Semantic Similarity

For deeper textual understanding, we also compute a **TF-IDF based cosine similarity** between the full resume and job description:

$$Sim_{TFIDF}(T,J) = \frac{\sum_{t\in T\cap J} tfidf(t,T)\cdot tfidf(t,J)}{\sqrt{\sum_{t\in T} tfidf(t,T)^2}\cdot\sqrt{\sum_{t\in J} tfidf(t,J)^2}}$$

Where $tfidf(t,D) = tf(t,D) \times \log\left(\frac{N}{df(t)}\right)$, $N$is the total number of documents, and $df(t)$is the document frequency of term t.

4.3 Application Conversion Rate (ACR)

The **Application Conversion Rate** measures the efficiency of the recruitment funnel:

$$ACR = \left(\frac{N_{submitted}}{N_{initiated}}\right) \times 100\%$$

Where:

- $N_{submitted}$: Number of successfully submitted applications.
- $N_{initiated}$: Number of unique resume upload/application initiation sessions.

4.4 Candidate Ranking Score (CRS)

Candidates are ranked for recruiters using the **Candidate Ranking Score**:

$$CRS = \alpha \cdot RMS(T,J) + \beta \cdot E_s + \gamma \cdot E_{dm} + \delta \cdot A_q$$

Where:

- $RMS(T,J)$: Resume Matching Score from Equation (1).
- E_s: Scaled Experience Score:

$$E_s = \min\left(1.0, \frac{Y_{exp}}{10}\right)$$

(Y_{exp}: years of relevant experience).

- E_{dm}: Education Match Score (0.0 to 1.0):

$$E_{dm} = \begin{cases} 1.0 & \text{if degree level matches or exceeds requirement} \\ 0.7 & \text{if related field} \\ 0.0 & \text{otherwise} \end{cases}$$

- A_q: Activity Quality Score (optional new term):

$$A_q = \frac{C_{applications} + 2 \cdot C_{interviews}}{M_{months}}$$

(normalised activity intensity over recent months).

- Weights satisfy $\alpha + \beta + \gamma + \delta = 1.0$(typical: 0.45, 0.25, 0.20, 0.10).

4.5 Overall System Effectiveness Score (OSES)

For holistic system evaluation, we define an **Overall System Effectiveness Score**:

$$OSES = 0.4 \cdot P_{parse} + 0.3 \cdot ACR + 0.2 \cdot (1 - L_{avg}) + 0.1 \cdot U_{sat}$$

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Where:

- P_{parse}: Resume parsing accuracy (0–1).
- ACR: Application Conversion Rate (normalized to 0–1).
- L_{avg}: Average normalized latency across API and chatbot responses.
- U_{sat}: User satisfaction score from post-interaction feedback (0–1).

V. SECURITY ENHANCEMENT DETAILS

Joblet.AI employs a comprehensive, multi-layered security architecture to safeguard sensitive user data, including personal resumes, candidate profiles, and company recruitment information. The system follows the principles of **defense-in-depth**, combining authentication, authorization, encryption, and secure data handling practices.

5.1 Authentication and JWT Validation

All client-server communications are secured through **Firebase Authentication**. Upon login (via Google OAuth or email/password), the client receives a **Firebase ID Token (JWT)**.

This token is sent in every API request using the Authorization: Bearer <token> header. The Express backend verifies the token using the Firebase Admin SDK:

```
const { getAuth } = require('firebase-admin/auth');
const decodedToken = await getAuth().verifyIdToken(idToken);
```

Token Validation Formula: The verification process checks token integrity using:

$$\text{TokenValidity} = \text{verify}(\text{Signature,PublicKey}) \wedge (\text{exp} > \text{currentTime}) \wedge (\text{iss} = \text{validIssuer})$$

Custom claims are added to the token to store user role (role: "applicant" or role: "recruiter"), enabling immediate role-based decisions.

5.2 Password Hashing for Recruiter Authentication

For recruiters using email/password authentication, passwords are never stored in plain text. Instead, they are hashed using a strong, memory-hard algorithm:

- **bcrypt** (with cost factor 12) or **PBKDF2** (with 100,000+ iterations) is used.

Password Hashing Security: The strength of the hashing can be expressed as:

$$\text{SecurityLevel} = \log_2(\text{KeySpace}) + \text{Iterations} \times \text{CostFactor}$$

Where:

- KeySpace represents the total possible password combinations.
- Higher iteration counts significantly increase resistance against brute-force and rainbow table attacks.

5.3 Transport Security (HTTPS/TLS)

All endpoints enforce **TLS 1.3** encryption. This ensures confidentiality and integrity of data in transit.

TLS Security Strength: The cryptographic strength is governed by:

$$\text{ForwardSecrecy} = \text{ECDH Key Exchange} \times \text{AES-256-GCM Cipher}$$

This configuration protects against man-in-the-middle (MITM) attacks and packet sniffing.

5.4 Data-at-Rest Encryption

- Uploaded resumes (PDFs) and company logos are stored in **Firebase Storage** and **Cloudinary**.
- Both services automatically apply **AES-256** server-side encryption.

- Additional client-side encryption can be applied using the Web Crypto API before upload.

Encryption Strength Formula:

$$\text{EncryptionSecurity} = 2^{256}(\text{for AES-256})$$

This provides an astronomically large key space, making brute-force attacks computationally infeasible.

5.5 Firestore Security Rules

Firebase Firestore uses declarative security rules to enforce data access at the database level. Key rules include:

JavaScript

Copy

```
rules_version = '2';
service cloud.firestore {
  match /databases/{database}/documents {
    match /applications/{applicationId} {
      allow read, write: if
        request.auth != null &&
        (request.auth.uid == resource.data.userId ||
         request.auth.token.role == 'recruiter');
    }

    match /resumes/{resumeId} {
      allow read, write: if request.auth.uid == resource.data.ownerId;
    }
  }
}
```

This ensures applicants can only access their own data, while recruiters have controlled access to aggregated candidate information.

5.6 Additional Security Measures

- **Rate Limiting & DDoS Protection**: Implemented using Vercel's built-in protections and custom middleware to prevent abuse.
- **Input Sanitization**: All user inputs are sanitized to prevent NoSQL injection and XSS attacks.
- **Audit Logging**: All critical actions (resume uploads, candidate scoring, job postings) are logged with timestamps and user IDs for forensic analysis.
- **Data Minimization**: Only necessary fields are stored; sensitive data is anonymized where possible.

Overall System Security Score (Conceptual):

$$\text{SystemSecurity} = w_1 \cdot \text{AuthStrength} + w_2 \cdot \text{Encryption} + w_3 \cdot \text{RBAC} + w_4 \cdot \text{Auditability}$$

where weights $w_i$sum to 1.0, typically prioritizing authentication and encryption.

These layered security mechanisms ensure Joblet.AI meets enterprise-grade standards while maintaining usability for both applicants and recruiters.

IV. EXPERIMENTAL SETUP AND EVALU ATION

This section presents the experimental environment, dataset characteristics, evaluation methodology, performance metrics, and quantitative results used to validate the effectiveness of Joblet.AI. The objective of the evaluation is to measure the accuracy of resume parsing, efficiency of candidate-job matching, chatbot responsiveness, and overall system reliability under realistic recruitment workloads.

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6.1 Experimental Environment

The Joblet.AI platform was deployed using a cloud-native architecture consisting of a React frontend, Express.js backend, Firebase services, and Gemini 1.5 Flash for conversational intelligence. The backend services were hosted on a Vercel serverless infrastructure, while user data, job postings, and application records were stored in Firebase Firestore. Uploaded resumes and company assets were maintained within Firebase Storage.

Hardware and Cloud Configuration

Component	Specification
Frontend	React.js + Tailwind CSS
Backend	Node.js + Express.js
Database	Firebase Firestore
Authentication	Firebase Authentication
Storage	Firebase Storage
AI Model	Gemini 1.5 Flash
Hosting Platform	Vercel Serverless Functions
Security Layer	TLS 1.3 + JWT Authentication

The system was evaluated over a period of four weeks under simulated recruitment activities involving both job seekers and recruiters.

6.2 Dataset Description

To ensure realistic testing conditions, a diverse resume dataset containing **1,500 resumes** was curated from publicly available templates and anonymized professional profiles.

Dataset Distribution

Sector	Number of Resumes
Software Engineering	620
Healthcare	280
Finance	250
Marketing	210
Human Resources	140

Resume Format Distribution

Format	Percentage
PDF	85%
DOCX	15%

The dataset included resumes with varying layouts, including:

- Single-column professional templates
- Two-column modern templates
- Academic CVs
- ATS-optimized resumes

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- Graphic-heavy infographic resumes

This diversity enabled comprehensive evaluation of the parsing engine under different formatting complexities.

6.3 Evaluation Methodology

The evaluation process consisted of four major stages:

- **Stage 1: Resume Upload**

Each resume was uploaded through the applicant interface. The uploaded document was automatically processed by the Resume Intelligence Engine.

- **Stage 2: Information Extraction**

The parser extracted:

- Candidate Name
- Email Address
- Phone Number
- Technical Skills
- Education Details
- Work Experience
- Certifications
- Projects
- **Stage 3: Ground Truth Verification**

Human evaluators manually labeled the correct information for every resume. These labels served as the ground-truth dataset against which parser outputs were compared.

- **Stage 4: AI Evaluation**

CareerBot and HireBot interactions were tested using predefined recruitment scenarios including:

- Job recommendation queries
- Resume improvement requests
- Candidate ranking tasks
- Job description generation
- Analytics interpretation

A total of **5,000 chatbot interactions** were conducted to evaluate conversational quality and response consistency.

6.4 Performance Metrics

The following metrics were used to evaluate system performance.

- **Resume Parsing Precision**

Measures the correctness of extracted fields.

$$Precision = \frac{TP}{TP + FP}$$

Where:

- TP = Correctly extracted fields
- FP = Incorrectly extracted fields
- **Resume Parsing Recall**

Measures the completeness of extraction.

$$Recall = \frac{TP}{TP + FN}$$

Where:

- FN = Relevant fields missed by the parser

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- **Parsing Accuracy**

$$Accuracy = \frac{Correctly\ Extracted\ Fields}{Total\ Ground\ Truth\ Fields} \times 100$$

- **Average API Response Time**

The mean latency observed across all backend API requests.

- **Chatbot Response Time**

Average time required for Gemini-powered assistants to generate responses.

- **System Availability**

Percentage of successful requests completed without failure.

6.5 Experimental Scenarios

To evaluate robustness, Joblet.AI was tested under multiple workload conditions.

- **Scenario A: Low Traffic**
- 50 concurrent users
- 200 daily applications
- **Scenario B: Medium Traffic**
- 250 concurrent users
- 1,000 daily applications
- **Scenario C: High Traffic**
- 1,000 concurrent users
- 5,000 daily applications

Performance metrics were recorded under each workload condition.

6.6 Quantitative Results

Resume Parsing Performance

Resume Type	Accuracy
ATS-Friendly	98.5%
Standard Professional	96.4%
Academic CV	94.7%
Two-Column Layout	91.0%
Infographic Resume	82.1%

The parser achieved highest accuracy on ATS-optimized resumes due to their structured formatting, while infographic resumes posed challenges because of embedded graphical elements and non-standard layouts.

Overall System Metrics

Metric	Value
Resume Parsing Accuracy	94.2%
API Response Time	120 ms
Chatbot Response Time	1.8 s
Application Conversion Rate	68.5%
System Success Rate	99.8%

The results demonstrate that the system exceeds all predefined Service Level Agreement (SLA) targets and maintains high responsiveness under realistic recruitment workloads.

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6.7 Discussion

The experimental results indicate that Joblet.AI effectively combines conversational AI and automated resume intelligence to improve recruitment efficiency. The 94.2% parsing accuracy demonstrates the reliability of the extraction engine, while the average chatbot response time of 1.8 seconds ensures near real-time interaction for both applicants and recruiters. Furthermore, the system maintained a success rate of 99.8%, highlighting the stability of the Firebase-Vercel deployment architecture.

Compared with traditional recruitment platforms, Joblet.AI reduces manual screening effort by automating candidate evaluation, ranking, and resume analysis through specialized AI agents. These findings validate the practicality of a dual-role conversational architecture for modern recruitment ecosystems.

IV. QUANTITATIVE PERFORMANCE METRICS

To evaluate the effectiveness of Joblet.AI, several quantitative metrics were measured across resume processing, chatbot interaction, API performance, recruitment workflow efficiency, and overall system reliability. The evaluation was conducted using a dataset of 1,500 resumes and simulated recruitment activities involving both applicants and recruiters. Results indicate that the proposed dual-role AI architecture successfully meets and exceeds the predefined Service Level Agreement (SLA) targets across all major performance indicators.

Resume Parsing Accuracy

Resume parsing accuracy measures the system's ability to correctly extract structured information such as candidate names, contact details, skills, education history, certifications, and work experience from uploaded resumes. The parser achieved an overall accuracy of **94.2%**, significantly exceeding the target threshold of **90%**. High accuracy was observed in ATS-friendly and standard professional resume formats due to their well-defined structure, while infographic-based resumes showed relatively lower extraction performance because of complex visual layouts and embedded graphical content. This demonstrates the robustness of the Resume Intelligence Engine across diverse document formats.

API Response Time

API response time represents the average duration required for backend services to process requests and return results. Across all evaluated endpoints, including authentication, job search, application submission, recruiter analytics, and resume processing APIs, the system recorded an average response time of **120 milliseconds**, outperforming the SLA requirement of **200 milliseconds**. The low latency can be attributed to the serverless architecture deployed on Vercel combined with Firebase Firestore's optimized document retrieval mechanisms.

Chatbot Response Time

The responsiveness of both CareerBot and HireBot was measured by calculating the average time taken to generate contextual responses. The conversational agents achieved an average response time of **1.8 seconds**, comfortably below the target threshold of **3 seconds**. This level of responsiveness ensures a near real-time interactive experience for users seeking career guidance, resume analysis, candidate evaluation, or recruitment insights. The integration of Gemini 1.5 Flash contributes significantly to maintaining low inference latency while preserving response quality.

Application Funnel Conversion Rate

The Application Conversion Rate (ACR) evaluates the effectiveness of the platform in converting job exploration activities into completed applications. Experimental observations revealed a conversion rate of **68.5%**, substantially higher than the target benchmark of **50%**. This improvement can be attributed to personalized job recommendations, resume optimization assistance, and conversational guidance provided by CareerBot, which collectively reduce application abandonment and improve user engagement throughout the recruitment journey.

System Success Rate

System success rate measures the percentage of requests completed successfully without server errors, authentication failures, or processing interruptions. Joblet.AI achieved a success rate of **99.8%**, surpassing the SLA target of **99%**.

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This high reliability demonstrates the effectiveness of the platform's cloud-native architecture, secure authentication mechanisms, and scalable backend infrastructure. The result indicates that the platform can sustain continuous operation under realistic recruitment workloads while maintaining service availability and data integrity.

Summary of Performance Results

Metric	Achieved Value	Target SLA	Status
Resume Parsing Accuracy	94.2%	≥ 90.0%	Pass
API Response Time	120 ms	≤ 200 ms	Pass
Chatbot Response Time	1.8 s	≤ 3.0 s	Pass
Application Conversion Rate	68.5%	≥ 50.0%	Pass
System Success Rate	99.8%	≥ 99.0%	Pass

Overall, the quantitative evaluation demonstrates that Joblet.AI delivers high accuracy, low latency, strong user engagement, and exceptional reliability. The results validate the effectiveness of the dual-role conversational AI architecture in supporting both applicants and recruiters while maintaining enterprise-grade performance standards.

V. COMPARISON WITH EXISTING SYS TEMS

To assess the practical value of Joblet.AI, we compared it against leading recruitment platforms including LinkedIn, Indeed, and Glassdoor. The comparison focuses on key recruitment functionalities such as user interaction, ATS scoring, recruiter assistance, analytics capabilities, and AI integration. While existing platforms primarily operate as job listing and application management systems, Joblet.AI introduces a conversational, AI-driven recruitment workflow that actively assists both applicants and recruiters throughout the hiring lifecycle.

Feature	LinkedIn	Indeed	Glassdoor	Joblet.AI
Primary User Interaction	Form-Based Search	Form-Based Search	Form-Based Search	Conversational AI Interface
Applicant Guidance	Limited	Limited	Limited	CareerBot Assistant
Recruiter Dashboard	Available	Available	Available	HireBot + Analytics Dashboard
Resume ATS Scoring	Paid Feature	Limited Support	Not Available	Free Integrated Scoring
AI-Powered Resume Feedback	No	No	No	Yes
AI Job Recommendation	Basic Recommendation Engine	Basic Recommendation Engine	Basic Recommendation Engine	Context-Aware CareerBot
Candidate Ranking	Manual Filtering	Keyword-Based Filtering	Manual Filtering	AI-Driven Ranking Score
Role Separation	Shared Environment	Shared Environment	Shared Environment	Strict Dual-Agent Isolation
Recruitment Analytics	Basic Metrics	Basic Metrics	Review-Based Insights	Predictive Analytics

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Feature	LinkedIn	Indeed	Glassdoor	Joblet.AI
Job Description Generation	Manual	Manual	Manual	AI-Assisted Generation
Real-Time Conversational Support	No	No	No	Yes
Open-Source Architecture	No	No	No	Yes

Adapted from the system comparison presented in the Joblet.AI evaluation.

[1] Comparative Analysis

Traditional Recruitment Platforms

Existing recruitment platforms primarily rely on search forms, filters, and manual interactions. Applicants typically search for jobs using keywords and location filters, while recruiters manually review resumes and shortlist candidates. Although these platforms provide extensive job databases, they offer limited personalized guidance and minimal automation during candidate evaluation. Recruiters often spend considerable time screening applications and creating job descriptions manually.

Advantages of Joblet.AI

Joblet.AI introduces a fundamentally different approach through its **dual-role AI architecture**. Instead of treating all users identically, the platform deploys two specialized agents:

- **CareerBot** assists applicants with job discovery, ATS score improvement, resume optimization, and career guidance.
- **HireBot** supports recruiters through candidate ranking, hiring analytics, application summaries, and AI-generated job descriptions.

This separation ensures that each user group receives role-specific intelligence while maintaining secure access boundaries between applicant and recruiter data.

Recruitment Efficiency Improvements

Compared to traditional platforms, Joblet.AI provides:

- Faster resume screening through automated parsing and scoring.
- Improved candidate-job matching using semantic similarity algorithms.
- Reduced recruiter workload through AI-assisted candidate evaluation.
- Enhanced applicant engagement via conversational guidance.
- Higher application conversion rates through personalized recommendations.

The experimentally observed **68.5% application conversion rate**, **94.2% resume parsing accuracy**, and **99.8% system success rate** indicate that the platform can significantly improve recruitment efficiency while maintaining high reliability.

V. FUTURE SCOPE

Although Joblet.AI demonstrates strong performance in resume parsing, candidate matching, and conversational recruitment assistance, several opportunities exist for further enhancement. Future developments will focus on improving AI intelligence, expanding platform accessibility, enhancing recruitment automation, and supporting global-scale hiring operations. These improvements aim to transform Joblet.AI from an intelligent job portal into a comprehensive AI-powered recruitment ecosystem.

1. Advanced AI-Powered Candidate Ranking

The current candidate ranking mechanism primarily relies on resume matching scores, experience levels, and educational qualifications. Future versions will incorporate graph-based semantic embeddings, transformer-based ranking models, and skill relationship networks to provide deeper candidate-job compatibility analysis. This approach

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will enable the system to identify hidden strengths and transferable skills that traditional keyword-matching techniques often overlook.

2. Semantic Multi-Job Recommendation Engine

At present, candidates are matched against individual job descriptions. Future enhancements will allow simultaneous matching across multiple positions using hierarchical semantic clustering and vector-based similarity search. This capability will help candidates discover a broader range of suitable opportunities while assisting recruiters in identifying talent pools for multiple openings within an organization.

3. Predictive Recruitment Analytics

Future versions of HireBot will integrate predictive analytics and machine learning models to forecast hiring trends, application conversion rates, candidate acceptance probabilities, and recruitment bottlenecks. Recruiters will receive data-driven recommendations to optimize hiring strategies, reduce time-to-hire, and improve workforce planning decisions.

4. AI-Powered Interview Assessment

A significant future enhancement involves introducing intelligent interview support systems. The platform will automatically generate role-specific interview questions, evaluate candidate responses, and provide recruiters with detailed assessment reports. Advanced implementations may include video interview analysis, communication scoring, sentiment detection, and technical skill evaluation using multimodal AI models.

5. Mobile Progressive Web Application (PWA)

To improve accessibility and user engagement, Joblet.AI will evolve into a Progressive Web Application (PWA). This enhancement will provide offline access, push notifications, faster loading times, and a native-app-like experience across mobile and desktop devices. Applicants will be able to receive instant updates regarding applications, interviews, and recruiter communications.

6. Multilingual Recruitment Support

As recruitment becomes increasingly global, future releases will support multilingual interactions through fine-tuned language models and automated translation systems. CareerBot and HireBot will communicate in multiple regional and international languages, enabling organizations to engage with diverse talent pools and improve accessibility for non-English-speaking candidates.

7. Intelligent Resume Enhancement Assistant

Future versions of CareerBot will provide more advanced resume optimization capabilities, including industry-specific recommendations, personalized career roadmaps, skill gap analysis, certification suggestions, and automated portfolio reviews. These features will help applicants continuously improve their professional profiles and increase employability.

8. Automated Interview Scheduling and Workflow Management

The platform will integrate calendar synchronization and workflow automation features to streamline recruitment operations. Recruiters will be able to automatically schedule interviews, send reminders, manage candidate pipelines, and coordinate hiring activities through intelligent scheduling agents. Integration with video conferencing platforms will further simplify remote hiring processes.

9. Integration with Professional Platforms

Future development plans include integration with major professional networking and recruitment platforms such as LinkedIn and enterprise HR systems. Such integrations will enable automatic profile synchronization, candidate sourcing, job distribution, and centralized recruitment management, reducing manual administrative effort.

10. Personalized AI Career Coach

A long-term vision for Joblet.AI is the introduction of a dedicated AI Career Coach that continuously monitors user progress, recommends learning resources, suggests certifications, tracks career growth, and provides personalized guidance based on industry trends and individual career objectives. This feature would transform the platform from a recruitment tool into a complete career development ecosystem.

11. Federated Learning and Privacy-Preserving AI

To enhance data privacy and security, future research will explore federated learning techniques that enable AI models to learn from distributed recruitment data without exposing sensitive candidate information. This approach can improve model performance while maintaining compliance with privacy regulations and enterprise security requirements.

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