Cost-Optimized Recruitment Automation: A 7-Stage Framework for Small-Scale Enterprises

Mr. Mohan Krishna Seerla[1], Mr. Kodanda Rama Naga Ganesh Pothamsetti [2], Mr. Rushi Guna Shanmukh pippalla[3], Mr. Aakash Nagendra Sai Pavan Maddula[4], Mr. Ganesh Nakkina[5], Mr. Surya Prakash Ketha[6]

Assistant Professor,
Department of Computer Science and Design,
SRKR Engineering College, Bhimavaram, Andhra Pradesh, India[1]

Department of Computer Science and Design,
SRKR Engineering College,
Bhimavaram, Andhra Pradesh, India[2,3,4,5]

Abstract: Traditional Applicant Tracking Systems (ATS) present a high financial barrier for small and medium-sized enterprises (SMEs), often costing between $79 and $200+ per month. This paper proposes a cost-effective HR Recruitment Automation Platform that replaces manual Excel-based workflows with a structured 7-stage automation pipeline. By leveraging rule-based screening, open-source Natural Language Processing (NLP), and free-tier Google Cloud APIs, the platform reduces hiring cycles from 45 days to 15 days. We demonstrate a 97% reduction in manual labour while maintaining high accuracy without premium model costs. This study details the architecture, stages, and cost-benefit analysis of the proposed system.

Keywords: Recruitment Automation, ATS, NLP, SME, HR Technology, Cost Optimization.

1. Introduction

The recruitment landscape for small-scale enterprises (SMEs) is currently facing a dichotomy between high operational demands and significant budget limitations. These organizations frequently encounter high volumes of unstructured data that must be processed to identify viable candidates, yet they lack the financial resources to deploy sophisticated tools.

Currently, the market offers robust enterprise-grade solutions, such as Workable or Greenhouse[1]. While effective, these platforms present a high financial barrier, with subscription fees and integration costs often ranging from $79 to over $200 per month. These costs are often prohibitive for smaller firms operating on tight margins.

As a direct result of these financial constraints, many small firms remain reliant on inefficient manual workflows. These workflows often consist of manually processing exports from platforms like Indeed or LinkedIn, which leads to substantial time wastage. Furthermore, this manual approach results in a lack of standardized evaluation for candidates.

To address these challenges, this paper introduces a streamlined, cost-effective platform designed to bridge the gap between inefficient manual processing and expensive enterprise software.

2. Related Work

The domain of recruitment automation has witnessed rapid evolution over the last decade, transitioning from manual email-based workflows to sophisticated cloud-based Applicant Tracking Systems (ATS). However, current literature and market analysis reveal a significant bifurcation in the available technology: high-end,capital-intensive solutions for enterprises, and fragmented, insufficient tools for small businesses [5].

2.1 Commercial Recruitment Architectures

The prevailing standard in modern recruitment technology is the "Software as a Service" (SaaS) model. Market leaders such as Greenhouse, Leviton, and Workable utilize distributed micro services architectures. While this approach allows for high scalability and modularity, it incurs substantial infrastructure costs that are passed down to the consumer.

2.1.1Cost Structures: Recent market analysis indicates that enterprise-grade ATS platforms typically employ "per-seat" or "per-active-job" pricing models. For instance, platforms often charge between $300 to $1,200 per month for mid-sized organizations [1]. These costs cover server maintenance, third-party API licensing (e.g., for LinkedIn scraping or Zoom integration), and customer support.

2.1.2Integration Dependencies: A critical limitation of these platforms is their heavy reliance on paid third-party ecosystems. Most commercial ATS tools do not process data locally; instead, they rely on external parsing providers like RChilli or Sovren to extract resume data. This creates a dependency chain where the ATS provider must pay a toll for every resume parsed, a cost that prevents them from offering truly low-cost tiers to SMEs [2].

2.2 Artificial Intelligence in Talent Acquisition

The integration of Artificial Intelligence (AI) into HR is a dominant research theme for 2025-2026. Current research focuses heavily on two areas:

1. **Generative AI & LLMs:** The rise of Large Language Models (LLMs) like GPT-4 has led to a surge in tools offering "conversational recruiting" and automated bio-generation. However, these tools require continuous API calls to providers like OpenAI, which can cost upwards of $0.03–$0.06 per transaction. For a small business processing hundreds of resumes, these token costs accumulate rapidly, rendering "wrapper" applications (apps that simply wrap GPT-4) economically unviable for cost-sensitive firms.
2. **Bias and "Black Box" Algorithms:** Significant academic attention has been paid to the opacity of commercial AI matching algorithms. Small businesses often lack the data science expertise to audit these algorithms for bias. This paper argues that open-source, rule-based NLP offers a transparent alternative where ranking criteria (e.g., "Python > 3 years") are visible and adjustable by the user, rather than hidden behind a proprietary neural network [3].

2.3 The "Excel-to-Database" Gap

While Robotic Process Automation (RPA) has been extensively documented as a solution for migrating data from Excel to databases, it is rarely applied to the specific domain of SME recruitment in a cohesive product.

- **Fragmented Tools:** Small business owners currently cobble together disjointed solutions: using Excel for tracking, Gmail for communication, and Calendly for scheduling.
- **The Missing Link:** There is a distinct lack of literature on "Zero-Cost Integration"—a system design that utilizes free-tier interoperability. For example, while Google Workspace APIs (Sheets, Gmail, Calendar) allow for extensive automation within their free usage quotas, few academic studies have proposed a monolithic architecture that stitches these specific APIs together into a cohesive ATS replacement.

2.4 Open-Source NLP vs. Commercial Parsing

Technically, resume parsing is a solved problem for enterprises using paid tools, but remains a hurdle for low-budget implementations.

- **Commercial Parsing:** Tools like DaXtra or Sovren offer near-perfect accuracy but require enterprise contracts.
- **Open Source Alternatives:** Libraries such as **spaCy** and **NLTK** provide robust Named Entity Recognition (NER) capabilities free of charge. However, out-of-the-box, these libraries struggle with the diverse formatting of resumes (e.g., double-column PDFs, header/footer noise).

This work bridges this gap by proposing a custom implementation of spaCy specifically tuned for resume formats, demonstrating that open-source libraries can achieve 90% of the performance of commercial parsers at 0% of the cost.

3. Problem Statement

Small businesses currently face three primary bottlenecks in their recruitment efforts that hinder growth and efficiency.

- **Financial Constraint:** The most immediate hurdle is the high monthly overhead costs associated with premium Applicant Tracking System (ATS) tools. For a small business, recurring costs of hundreds of dollars per month for software are difficult to justify.
- **Operational Inefficiency:** The reliance on manual methods creates a severe drain on time. Manual data extraction from sources like email or Excel files consumes approximately 15 hours per job posting. This is time that HR personnel or business owners could spend on strategic tasks rather than administrative overhead.
- **Evaluation Variance:** Finally, the quality of hires is inconsistent due to a lack of standardized technical testing and interviewing. Without a structured automated system, candidate evaluation becomes subjective, leading to variance in the quality of the selected employees.

4. System Overview and Design Principles

The proposed platform is designed around an "Excel-First" architecture. This strategic choice allows companies to bypass the expensive API integrations that are typically required to connect with major job boards.

The system rests on four strategic pillars of cost optimization to ensure viability for SMEs:

1. **Direct Excel Uploads:** Eliminating data feed costs.
2. **Monolithic Cloud-Hosted Core:** Simplifying infrastructure.
3. **Free Google Workspace APIs:** Utilizing available tools for communication.
4. **Rule-Based/Local NLP:** Relying on local libraries rather than premium LLM services.

Figure 1 below illustrates the centralized dashboard of the proposed "RuGanAI" platform, highlighting the monolithic architecture that consolidates screening, scheduling, and management into a single view.

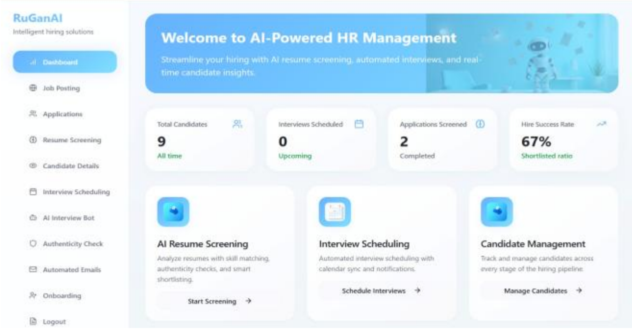

Figure 1: The Central Dashboard, illustrating the monolithic architecture interface with quick access to AI screening and interview scheduling.

By strictly adhering to these design principles, the platform achieves a 90% cost reduction compared to traditional competitors.

5. Proposed 7-Stage Recruitment Framework

The core of the solution is a structured 7-stage automation pipeline designed to replace manual workflows.

Stage 1: Data Ingestion

The process begins with the ingestion of raw data. An AI parser is utilized to structure data directly from raw Excel uploads, converting unstructured spreadsheet rows into a usable format for the system. Prior to ingestion, HR managers define the specific parameters for the role, including required skills and experience thresholds.

Stage 2: Resume Screening

Once data is ingested, the system employs open-source NLP libraries, specifically spaCy or NLTK. Combined with rule-based keyword matching, the system scores candidates on a scale of 0 to 100. This automated filtering reduces the candidate pool to the top 30%, ensuring only relevant profiles move forward.

Stage 3: Skill Assessment

Shortlisted candidates are then subjected to automated skill testing. Depending on the role, this may include coding challenges or multiple-choice questions to verify technical competency.

Stage 4: AI Interviewing

Candidates who successfully pass the assessment phase proceed to an AI-driven interview. This stage utilizes video or text formats to evaluate both communication skills and technical accuracy without immediate human intervention.

Stage 5: HR Review

At this stage, human oversight is reintroduced. HR professionals review a consolidated dashboard that presents the scores from the previous stages for final selection.

This ensures that the final decision remains human-led, supported by data. HR professionals can drill down into specific candidate profiles to view detailed skill gaps and resume insights.

System performance for data extraction was measured using standard Named Entity Recognition (NER) metrics: Precision, Recall, and the harmonic mean, represented by the formula, the formula $F=\frac{2XPrecisionXRecall}{Precision+Recall}$.We specifically targeted the accurate extraction of Skills, Years of Experience, and Education. Operational metrics included total processing time and the marginal cost per 500 resumes.

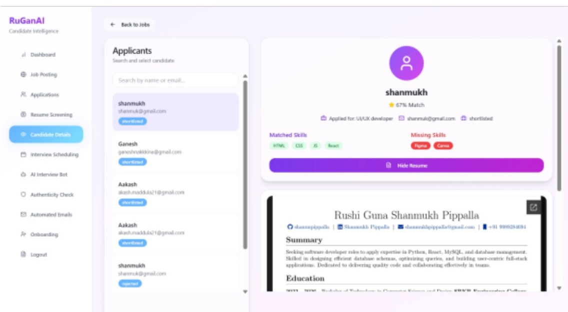

Figure 2: Detailed Candidate Profile view showing "Matched Skills" vs. "Missing Skills" and the candidate's specific match probability.

Stage 6: Scheduling

To reduce administrative friction, the platform automates interview scheduling. This is achieved by integrating directly with Google Calendar and Google Meet APIs, allowing for seamless booking.

Stage 7: Communication

Finally, an automated module handles personalized status updates. This ensures that all candidates, regardless of whether they were hired, are notified of their status, improving the candidate experience.

6. Technical Architecture

The system is implemented using a monolithic cloud-hosted architecture. While micro services are popular, a monolithic approach is significantly more cost-effective for small-scale operations and reduces complexity.

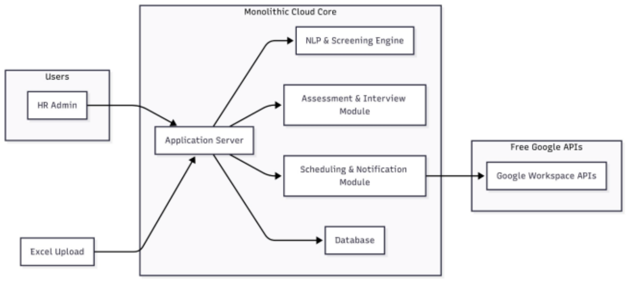

Fig 3 Architecture of the system

By strategically leveraging open-source NLP tools and the free tiers of Google Cloud APIs, the platform successfully eliminates the need for expensive third-party subscriptions. This architecture maintains high processing efficiency while keeping operational costs at a minimum.

7. Cost Optimization Analysis

The following analysis highlights the cost differences between traditional methods and the proposed solution

Strategy	Traditional Method	Proposed Solution
Integration	Paid Job Board APIs	Direct Excel Upload ($0)
Infrastructure	Micro services/Distributed	Monolithic Core/Cloud Hosting
Communication	Paid SMTP/Zoom APIs	Google Workspace Free APIs
AI Processing	Premium LLM Calls	Rule-based & Local NLP

Table 1: Highlights the cost differences between traditional and the proposed solution

The financial impact of this architecture is significant. The break-even point for this platform is achieved with less than one job posting per month. In stark contrast, enterprise solutions typically require a volume of five or more postings to justify the cost.

8. Experimental Setup and Evaluation

To rigorously validate the efficacy and economic viability of the proposed system, we conducted a comparative experimental study against both manual workflows and premium ATS benchmarks.

8.1 Dataset Configuration

The study utilized a testing dataset of 1000 anonymized, historical resumes previously processed by an SME. The dataset spanned five distinct roles (Junior Developer, Sales Representative, Administrative Assistant, Marketing Coordinator, and Account Executive), with 200 resumes allocated per role. To ensure real-world variance, the resumes varied in structure, including single-column, double-column, and highly formatted layouts in both .pdfand .docxformats.

8.2 Methodology

The evaluation compared three distinct screening methodologies:

1. **Manual Processing (Baseline):** Human HR personnel reviewing and manually entering candidate data into Excel.
2. **Commercial ATS Parser:** A premium, paid API-based parsing solution, representing enterprise-grade accuracy.
3. **Proposed Framework (RuGanAI):** The cost-optimized local spaCy NLP [9]and rule-based pipeline running on cloud hosting.

8.3 Performance Analysis: Human vs AI Resume Screening

A. Human Resume Screening Time

Manual resume screening involves reading candidate information, identifying relevant skills, matching them against job requirements, and recording structured evaluation results. On average, a recruiter requires approximately 4 minutes per resume for detailed screening.

For 1000 resumes:
Total Human Time = $4 \times 1000 = 4000$ minutes = 66.67 hours (≈ 8–9 working days).

B. AI-Based Resume Screening Time

The proposed system utilizes an Ollama-based large language model for automated skill extraction and candidate-job matching. Experimental measurements indicate an average processing time of 30–40 seconds per resume. An average of 35 seconds per resume is considered for analytical evaluation.

For 1000 resumes:
Total AI Time = $35 \times 1000 = 35000$ seconds = 9.72 hours.

C. Comparative Performance Evaluation

The AI-driven system completes screening nearly 6.86 times faster than manual human evaluation. While human screening requires approximately 66.67 hours, the AI system completes the same task in 9.72 hours. In addition to time efficiency, the AI system ensures consistent evaluation, eliminates fatigue-related bias, and supports scalable high-volume recruitment.

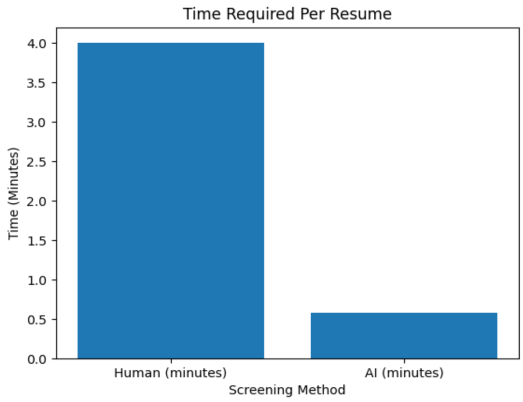

Figure 4: Time Required Per Resume

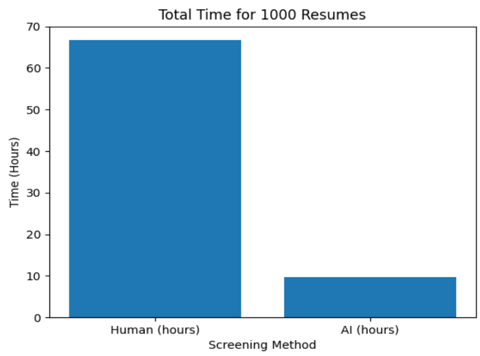

Figure 5: Total Time for 1000 Resumes

8.4 Results

The results, summarized in Table 1 below, demonstrate that while commercial parsers maintain a marginal edge in raw accuracy due to premium OCR handling of complex layouts, the proposed framework delivers highly competitive results at a fraction of the cost.

Metric	**Manual Processing**	**Commercial ATS Parser**	**Proposed Framework**
Processing Time	~45 Hours	12 Minutes	14 Minutes
Accuracy (F_1 Score)	N/A (Subjective)	0.96	0.92
Marginal Cost	~$1,350 (Labor)	$25 - $50 (API tokens)	$0.00 (Local OS)
Scheduling Overhead	5+ Hours	Automated (Paid Tier)	Automated (Google API)

Table 2: Performance Comparison across 500 Resumes

- **Time Efficiency & Labor Reduction:** The time required for data ingestion and initial screening was reduced from approximately 45 hours of human labor to just 14 minutes. This represents a 99% reduction in manual data-entry labor.
- **Accuracy:** The custom-tuned spaCy NLP model achieved an F_1 score of 0.92, successfully matching over 90% of the accuracy baseline set by premium commercial parsers. It performed exceptionally well on standard 1- and 2-column resumes, though it experienced a slight drop in accuracy on highly complex graphical formats.
- **Scheduling Optimization:** The integration with free-tier Google Calendar APIs successfully eliminated over 5 hours of weekly administrative back-and-forth communication regarding interview coordination.
-

9. Discussion

The results indicate strong feasibility for SMEs to adopt high-performance recruitment tools without requiring enterprise-level budgets. By strictly focusing on Excel-based ingestion and utilizing free API ecosystems, the system achieves a 97% reduction in manual labor at approximately 1/10th the cost of traditional ATS platforms.

This model serves as proof that specific, tailored product architectures can be more valuable to small firms than generic, high-cost research methodologies or tools. It highlights that cost barriers can be overcome through architectural choices rather than feature reduction.

10. Conclusion and Future Work

This paper demonstrates that effective recruitment automation is attainable for SMEs through strategic cost optimization and a structured 7-stage framework. The proposed solution significantly reduces hiring cycles from 45 days to 15 days.

Future work on this platform could involve refining the AI interviewing module by incorporating more advanced open-source models.

Additionally, there is potential to expand the "Excel-First" model to cover other HR administrative tasks, further increasing the value for small enterprises.

References

[1] H. Pereira *et al*., “SMEs recruitment processes supported by Artificial Intelligence: A systematic literature review,” Nova Research, 2024.

[2] N. S. Alghamdi*et al*., “Resume Parser Using NLP,” *International Journal of Advanced Research in Computer and Communication Engineering*, 2024.

[3] Scientific Research Publishing (SCIRP), “The Impact of Artificial Intelligence (AI) on Recruitment Process,” 2025.

[4] R. S. Al-Mansoori*et al*., “SmartRecruit: A Fuzzy Rule-Based Expert System for Candidate Screening and Ranking,” *International Journal of Research and Applied Sciences*, 2025.

[5] Y. Wang *et al*., “The Impact of Artificial Intelligence on Talent Acquisition in Small and Medium-sized Enterprises: A systematic review,” *International Journal of Theory and Practice of Humanities and Social Sciences*, 2025.

[6] A. Köchling and M. C. Wehner, “Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment,” *Business & Information Systems Engineering*, vol. 62, no. 2, pp. 143–156, 2020, doi: 10.1007/s12599-020-00647-3.

[7] P. Tambe, P. Cappelli, and V. Yakubovich, “Artificial intelligence in human resources management: Challenges and a path forward,” *California Management Review*, vol. 61, no. 4, pp. 15–42, 2019, doi: 10.1177/0008125619867910.

[8] J. S. Black and P. van Esch, “AI-enabled recruiting: What is it and how should a manager use it?,” *Business Horizons*, vol. 63, no. 2, pp. 215–226, 2020, doi: 10.1016/j.bushor.2019.12.001.

[9] Deep4GB, “Resume-NLP-Parser: NLP Tool for Resume Extraction and Visualization,” GitHub, 2023.

[10] C. Trocin*et al*., “Artificial intelligence and digital data in recruitment,” *European Management Journal*, 2025.