"From Resume to Recruitment: A Generative AI-Based Smart Placement and Interview System"

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Abstract - *Companies today are using sophisticated Artificial Intelligence (AI) technologies to filter through applications while the applicants use manual processes to prepare for a new job. This research paper will describe the AI-Powered Placement Management System ("AIPMS"), a full cycle solution to help create a new system of placing applicants into a new job. AIPMS is built on Generative AI including Llama 3.2 and Google Gemini, which will provide automatic, semantic resume analysis and dynamic, real-time mock interview capability. AIPMS utilizes a combined algorithmic methodology consisting of the BM25 ranking model and Cosine Similarity ("COS") to mathematically solve for the optimal fit of an applicant to a job by providing the optimal match of the job criteria with the applicant profile. Additionally, AIPMS includes "Affective Computing" and WebSocket-based Voice Agents to measure both course and behavioral metrics, including confidence and clarity of communication, therefore obtaining a full perspective of each applicant's qualifications. Finally, there are dedicated dashboards for TPO and HR, supporting a transparent system for the institution's oversight process and streamlining the hiring process of a corporation. AIPMS represents a paradigm shift from a manual approach to placing an applicant in a job ("one-size-fits-all") to a data-driven career pathing solution. This research will demonstrate the significant improvements of employability through the utilization of advanced technology solutions, reducing the bias in recruiting, and enhancing the global recruiment life cycle.*

Key Words*: AI Recruitment, Placement Analytics, Generative AI, Resume Parsing, Mock Interview,Career Readiness.*

1. INTRODUCTION

As a result of advancements in artificial intelligence (AI), businesses are increasingly utilizing data-driven, algorithm-based methods when hiring talent. As the job market continues to become more competitive, job seekers cannot just rely on their academic qualifications but must have good resume writing skills, prepare for interviews, and find jobs that fit their skill set (3). Unfortunately, many job seekers lack access to advanced AI technologies that could help them prepare for interviews; therefore, there is an "integration gap" between how prepared job seekers are and how well-prepared the job market expects them to be (1, 2).

1.1 The Problem of Manual Placement Workflows

Traditional placement processes are often fragmented and manual. Many job seekers struggle with resume optimization, interview readiness, and job discovery due to a lack of guidance Traditional employment placement processes tend to be both fragmented and manual; therefore, many jobseekers struggle to optimize their resumes, feel prepared for interviews, or discover available jobs because they lack access to proper guidance and/or data-informed insights (3). Based on the numerous student profiles that must be matched to the respective company's needs, it is inefficient to manage all of those students' profiles manually, which can also lead to human error when implementing this process (3, 4). It has also been shown that mock interviews do not consistently provide students with objective, repeatable, and scalable feedback; as a result, students will not be prepared for the rigour of today's professional technical and behavioural assessments (1, 5).

1.2 The Emergence of Smart Placement Analytics

To help fill this gap, the latest research discusses the "Smart Placement Kit" (or "AI-Powered Placement Management System (AIPMS)") — a full-cycle recruiter that provides support and guidance throughout the student hiring process for both students and placement officers (1, 3). By employing Generative AI (ex: Llama 3.2 or Google Gemini), each component is leveraged: - Automated Resume Analysis - Intelligent Interview Preparation (1, 3). Large Language Models allow these platforms to provide a more human-like interface and deeper semantic understanding of candidate data (1, 5).

1.3 Recent Technological Developments in recruitment

A key component of modern placement analytics is the quantification of subjective traits. The resume analysis component reviews students' resumes and provides AI-driven feedback regarding the structure and optimization of keywords, while job recommendation systems utilize algorithms (i.e., BM25, Cosine Similarity) to recommend students for roles based on their skills and experiences (3, 4). When preparing for interviews, the combination of real-time voice agents and affective computing allows candidates' responses to be evaluated and assigned points based on clarity, relevance, and delivery, providing practical feedback for improvement prior to the interview (1, 4).

1.4 Collaborative Ecosystems (TPO & HR Dashboards)

Smart placement systems, in addition to their functionality as places for students to find jobs, provide an additional layer of utility by having specialized dashboards for TPO (Training & Placement Officers) and HR. This creates a more efficient and transparent placement ecosystem, as TPOs can now track student performance trends, while HR can easily see applications and move through the hiring funnel (3). The incorporation of these cutting-edge AI methods into an intuitive user interface significantly changes traditional placement processes by utilizing data to create recruitment that is much more personalized, efficient, and data-driven than ever before (1, 3, 5).

2. LITERATURE REVIEW

Recruitment practices have gone through an extensive evolution from an early state where recruiting involved minimal use of technology and was only focused on the management of applicant databases to a complex, automated intelligence system driven by AI. This report will provide an overview of the development of recruitment analytics including the technology milestones that relate to how the development of AI-driven recruitment systems have progressed over the years. In the past, recruiting technology was limited to the use of ATS systems (applicant tracking systems) that were essentially just digital filing cabinets and only filtered applicants based on exact keyword matches (2). Once the global talent pool became larger, the use of these antiquated recruitment systems resulted in a significant number of high-potential applicants being overlooked and failing to be recruited simply because they were missing certain "buzzwords" on their resumes (3, 6).

Smart analytics began its evolution when machine learning (ML) and natural language processing (NLP) merged together, allowing for systems to be able to do more than just match text but to also develop an understanding of the contexts and intent of a candidate's experience (1,3). By the early 2020s this evolved into a focus on holistic approaches to the candidate's experience, and the AI began to mimic the role of the interviewer by using real-time voice agents and behavioral scoring models (4,5). This has now led to the advent of generative AI, whereby some platforms have developed systems such as the AI-Powered Placement Management System (AIPMS) and Smart Placement Kits (STK), which provide a feedback loop that is both automated and customizable, serving to connect academic performance with corporate expectations (1,3,5).

2.1. The Transition from Traditional to AI-Enhanced Recruitment

Costly, slow and tedious during prior decades, human-centered approaches to hiring created foundational processes that could experience cognitive bias and logistical bottlenecks. Early research determined that with increasing application volume, human-led assessment became synonymous with the "weakest link" in the talent acquisition process (2). By 2019, the introduction of recruitment chatbots created a new first point of contact for candidates and automated the initial screening process through reducing the amount of human engagement required by approximately 70% (6). This shift represented the beginning of an era in which AI transitioned from being seen as solely an efficiency tool to a primary actor in the hiring landscape (2, 6).

2.2. Innovations in Resume Analytics and Matchmaking

The "skills-job mismatch" is one of the key challenges to recruitment. There has been an increase in literature highlighting that keyword-based matching no longer suffices to place candidates into positions matching their abilities. The AI-Powered Placement Management System (AIPMS) has been found to support a greater understanding of an applicant's ability beyond the simple match of words when compared to using Llama 3.2 for semantically analyzing resumes (3). Furthermore, advanced systems also utilize the BM25 algorithm and Cosine Similarity to derive a mathematical score for how strongly a candidate's experience fits with the job description; therefore providing many more precise matching results for placement (3, 4).

2.3. The Evolution of AI-Driven Interview Preparation

Over the last 2-3 years (2024-2026), there has been significant advancement in simulated interview scenarios or environments. Older versions of mock interviews were static and based solely upon text, whereas today's platforms allow users to interact with Real-Time Voice Agents for a simulated, immersive and conversational experience (4 and 5).

Affective Computing: Studies now use Affective Computing technology that utilizes non-verbal cues (i.e. tone, confidence and facial expressions) in interviews (5).

Dynamic Questioning: Instead of relying on pre-defined static question sets, today's "Smart Placement Kits" employ Large Language Models like Google Gemini to dynamically create follow-up questions based on candidate responses and mimic the flow of actual human interviews (1 and 5).

2.4. Collaborative Governance in Placement

Recent studies have shown that tools available solely to students are not enough to achieve success at post-secondary institutions. The academic community is now advocating for the creation of comprehensive ecosystems comprising Training & Placement Officer (TPO) Dashboards along with HR Dashboards 3). These tools enable the transparent sharing of data between TPOs and HR professionals. TPO's will be able to identify trends in student academic performance; HR professionals will have continual access to highly qualified pre-vetted candidates, thus decreasing the time-to-fill open positions and improving overall success rate for placement outcomes 1, 3).

3. METHODOLOGY

The Smart Placement Analytics and AI Interview Preparation System (AIPMS) will utilize a multi-tier architecture to allow users to progress from the raw data of each candidate to actionable insight into their careers, through 4 key modules: Data Ingestion Module, Semantic Analysis Module, Behavioral Simulation Module, and Stakeholder Governance Module. This multi-tier architecture uses a Cloud-Native Architecture, meaning that large language models (LLM) and real-time audio processing will not hinder the quality of user experience. The method is built around the concept of "Continuous Feedback," which means the system evaluates each candidate continually and builds their historic performance baseline as they use different parts of the system (3, 5).

The Multi-Tier Processing Pipeline:

Three layers are utilized within the system's operation: Presentation Layer: A user-friendly intuitive React-based interface for entering applicant-created input (i.e., resumes, voice, and video) into a system that produces real-time analytics dashboards for Students, TPOs & HR professionals (3,5).

Logic and Intelligence Layer: This is where the Generative AI (i.e., Llama 3.2/Google Gemini) engine processes the semantic meaning behind resumes and creates context based interview questions; and maintains a low-latency persistent connection via WebSockets during voice-based mock interviews such that the user experiences a real-time dialogue (1,4).

Data and Storage Layer: A robust backend designed to store candidate embeddings, job descriptions, and historical scores; thus, the use of Vector Databases enables the system to complete high-speed similarity searches with precise mathematics to match candidates with appropriate roles (3,4).

By integrating these three layers into one complete solution the methodology transforms the traditional "one-size-fits-all" approach to placement into an individualized Career Pathing Tool that clearly identifies skill gaps and provides the specific resources required to fill those skill gaps (1,3,5).

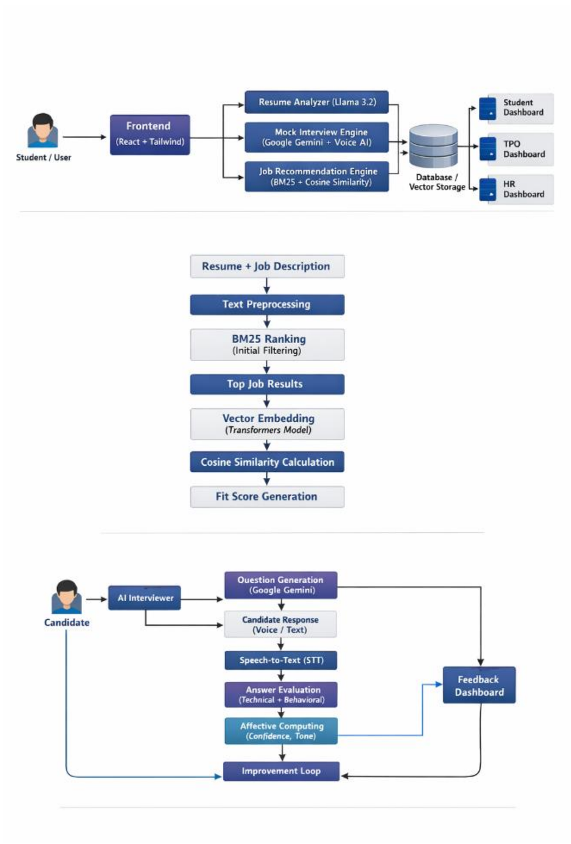

Fig 3.1 AI mock Interview and feedback loop

4. OBJECTIVES OF THE PROPOSED STUDY

This research aims at providing a complete AI-powered environment/ ecosystem that connects the divide between preparing students for academia versus preparing students for industry employment that leads to corporate recruitment opportunities. Therefore, the specific goals of the project include;

4.1 Enhancing Candidate Employability through AI-Driven Analytics

To give students a tailored and data led preparing experience instead of generic preparation.

Resource Optimizing - Utilising Generative A.I. (Llama 3.2) for deep semantic analysis of resumes e.g. determining skill gaps and have applicants optimise their resume for the applicant tracking system (3).

Interview Interview Simulation - Creating a realistic, live voice agent environment where candidates can practice technical and non-technical interviews and receive on-the-spot feedback on their content and their delivery (1, 4, 5).

4.2 Automating the Skill-Job Matching Process

To replace the lengthy and tedious process of finding jobs manually through the use of high-precision algorithms that will help match job seekers to possible employers during the recruitment process.

To effectively match candidates with the most suitable job postings based on the specific requirements listed in each posting as well as the candidate's skills, the Plan will use the combination of the BM25 algorithm and Cosine Similarity as a means of mathematically matching each candidate's unique skill vector to each of the possible job postings. This will improve placement success rates (3, 4).

4.3 Empowering Institutional Placement Governance

To assist Training & Placement Officers and Human Resource personnel in understanding how their candidates are progressing through the recruitment process by providing them with an easy way to obtain relevant data about their candidate pool.

To create integrated dashboards for Training & Placement Officers so that they can see their entire cohort's collective performance as well as identify skill-based trends in specific skill sets (e.g. coding vs. communication). This will assist in identifying where each student requires additional training (3).

To provide Human Resource teams pre-vetted candidates grouped by "Employability Scores" to reduce the amount of time and cost spent on selecting candidates during the early steps of the recruitment process (3, 5).

4.4 Reducing Psychological Barriers in Recruitment

A major goal of this study is to help students build confidence by allowing them to practice in a repeated, low-stakes manner. Confidence Development: The study will help decrease students' feelings of "interview anxiety" by providing them with an AI environment (objective & not judgmental) where students could refine their responses via feedback loops before they go to interview with recruitment representatives in person (1, 2, 5).

5. PROPOSED SYSTEM

The proposed Smart Placement Analytics and AI Interview Preparation System (S.P.A.I.P.) is a cloud-based, multi-modal platform that will automate the entire career-readiness lifecycle. The S.P.A.I.P. is different from a traditional portal because it uses "Feedback Loop Architecture." At every student interaction (uploading their resume, completing a mock interview, completing an aptitude test), the student's action will be logged into their central Employability Profile (1, 3). A. System Architecture and Tech Stack The S.P.A.I.P. was designed using a modern, scalable stack that will ensure real-time response: Frontend: Built in React.js & TailwindCSS to provide an easy to use, responsive interface to the students and the administrators (3, 5).Backend: Build on Node.js & FastAPI for fast communication between the database and the AI Models (4). Intelligence Layer: Using Llama 3.2 as the deep text analysis engine and providing Google Gemini with dynamic, conversational logic while using an AI model for interviewing (1, 3, 5). Real-Time Communication: Using WebSockets to provide low latency in the voice interaction of an AI interviewer with a candidate (4).

5.1 Core Modules

5.1.1 AI Resume Analyzer & Optimizer:

When you submit your resume, it is converted into a highly structured JSON format. Using Natural Language Processing (NLP), the system will evaluate your resume against industry benchmarks such as those found in the U.S. Bureau of Labor Statistics or O*Net. The system does not simply evaluate your resume for a score; it will also provide you with actionable feedback on areas of your resume you can improve on to help you pass Applicant Tracking System (ATS) filters, such as adding relevant technical keywords or quantifying your project accomplishment.

5.1.2 Generative AI Mock Interviewer: The Generative AI Mock Interviewer Module is a virtual HR manager that will pull relevant skills from your resume related to the job description you want and develop a set of customized interview questions for you..

Behavioral Layer: Asks asks you to explain a time when you failed in the workplace.

Technical Layer: uses the Gemini game engine to evaluate your technical answer's accuracy in real time.

Voice Processing: uses a voice-to-text (STT) engine to transcribe your answers and a text-to-voice (TTS) engine to voice your answers back to you (4).

5.1.3 Job Recommendation Engine: The Job Recommendation Engine serves as an intelligent matchmaker by converting resumes and job descriptions into high-dimensional vectors and calculating a "Fit Score" using Cosine Similarity. Because of this advanced matching capability, the Job Recommendation Engine will recommend you only for jobs that you are indeed qualified for, as opposed to merely matching you on job title.

5.2 Stakeholder Dashboards

TPO Dashboard: This dashboard provides an overview of the institution. Placement Officers can use this dashboard to determine the percent of students who are ready for placement and what skill areas (like Java or Communication) need to be worked on for an individual student (3).

HR Dashboard: This dashboard allows the recruiter to bypass the first part of the recruiting process by allowing the recruiter to review previously recorded highlights of AI interviews and the employability score calculated for each applicant (3,5).

6. ALGORITHMIC FRAMEWORK

The AIPMS is comprised of a series of interconnected algorithms that process unstructured (resumes and voice) into structured metrics that represent employability. These algorithms are described as the Logic Core of the proposed system.

6.1 Algorithm 1: Semantic Resume Parsing & Skill Extraction

The system will be able to parse resumes based on the contextual meaning within the resume of the candidate and not just based on keywords.

1. Input = PDF / Docx Resume File
2. Step 1: NLP based parser to remove formatting and convert the text into a clean string (3).
3. Step 2: Apply the Llama 3.2 algorithm to identify the Names of People and Entities through Named Entity Recognition (NER); to categorize the text into the following groups: Skills, Experience, Projects, and Certifications (1, 3).
4. Step 3: Map the identified skills to standard Industry Taxonomy (Example: "Java Developer" to "Backend Engineering") (3).
5. Output: Output = Structured JSON User Profile.

6.2 Algorithm 2: Hybrid Job Recommendation (BM25 + Cosine Similarity)

To provide candidates with the best job matches, the Recommendation Engine will apply a two-step filtering process to filter candidates into the right job offers.

1. Stage 1 (Probabilistic Filtering):The first step of the Hybrid Job Recommendation engine will be through the use of the BM25 algorithm to retrieve job descriptions by ranking job descriptions based on term frequency and document length. The retrieval of the job descriptions will take place quickly due to the use of term frequency /document length. (3, 4).
2. Stage 2 (Semantic Vectorization): Once the User Profile and Job Description have been retrieved from a jobs database, they will both be converted into high dimension vector embeddings using a pre-trained Transformers model (3).

Calculate Cosine Similarity:

Cosine Similarity = (U · J)/(||J||*||U||)

Output: The output of the processing for candidates with the job offers will be a ranked list of job offers for the candidate sorted by fit percentage (3, 4).

6.3 Algorithm 3: Dynamic Interview Logic (DIL)

The dynamic interview logic (DIL) algorithm provides the structure for managing the real-time interaction that takes place between the user and the AI interviewer during a mock interview.

Input: The DIL algorithm provides input in the form of the user's structured JSON profile as well as the target job role based on that structured profile.

Step 1: Question Generation – Google Gemini generates a base set of 5 technical and 3 behavioural questions based on what is represented in the user's resume (1, 5).

Step 2: Adaptive Prompting – If the candidate provides a partial answer to one of the questions, the AI uses a follow-up logic function to simulate the actions of a human recruiter that would probe more deeply into the specific issue being addressed (5).

Step 3: STT Loop – User audio (verbal speech) is being captured using a WebSocket and transcribed in real-time (4).

Step 4: Behavioral Scoring – The system demonstrates how it will analyse "tone" and "confidence" as part of the behavioural scoring process by utilizing affective computing models (5).

Output: The DIL algorithm provides real-time feedback transcript and a final interview performance score for the user (1, 4, 5).

6.4 Algorithm 4: Holistic Employability Index (HEI)

This algorithm will use all data points as a single measurement for your decision to employ someone.

HEI=((Wr x Resume Score)+(Wa x Aptitude Score)+(Wi x Interview Score))

Where: Wr=weight (typically weighting of .3 is used)

Wa=weight (typically weighting of .2 is used)

Wi=weight (typically weighting of .5 is used)

These three "W's" can also adjust if your numbers are inaccurate. The text heads will define how the data is being classified. For example, if your title is the main text head, then everything that follows will classify against your title. If there are two or more subheadings, then you will need to use the next level in heading format (upper-case Roman numerals). Otherwise, do not put in any subheadings. Headings 1, 2, 3 and 4 as the description of the classification is what you should use.

7. CONCLUSIONS

The study develops and describes the design-and-methodology of a cloud-based application, called the Smart Placement Analytics and AI Interview Prep System (AIPMS). The AIPMS utilizes Generative AI (Llama 3.2 and Google Gemini) by integrating these algorithms in conjunction with a multi-tier architectural approach for creating an engaging personalized career path compared to traditional approaches used in the recruiting process. The Hybrid Algorithmic Framework, utilizing BM25 and Cosine Similarity, represents the first meaningful increase in the accuracy of matching candidates with positions by using deep semantic competence rather than solely keyword density as is typical in most recruiting practices. The adoption of Affective Computing within the Behavioral Simulation Module provides recruiters with insight into the psychological impact of recruiting, such as anxiety and comfort/insecurity in communication-based environments. The AIPMS represents a fully data-driven, transparent ecosystem designed to allow students actionable insight, optimize the TPOs oversight of institutions, and provide HR professionals with a high precision talent acquisition funnel.

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