SMART - System for Matching And Ranking Talents

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Abstract. Personnel recruitment and selection is a critical challenge for organizations, where speed and quality of choice directly affect the ability to identify and hire top talent in an increasingly competitive labor market. Current practices rely on manual evaluations performed by recruiters according to their individual experience and limited to a single job position. This approach presents several drawbacks, including slow decision-making processes, susceptibility to cognitive biases, a high risk of false positives and false negatives, and the inability to assess candidates against multiple positions simultaneously. This paper presents SMART (System for Matching And Ranking Talents), an HR Intelligence platform integrating a no-code BPM (Business Process Management) engine for digital modeling and execution of the recruitment workflow, with a multi-agent AI system supporting candidate evaluation. The no-code approach ensures organizational flexibility and seamless integration with existing enterprise environments, distinguishing SMART from traditional vertical solutions. Dedicated HR agents automate parallel Screening, Job-Matching, and Ranking phases, analyzing CV content alongside complementary sources—LinkedIn profiles, publicly available information, certifications, and validated hard/soft skills—against the ideal job profile, ensuring fairness and impartiality. The system adopts a symbiotic human-AI paradigm, where agents provide suggestions, feedback, and explainable results to support rather than replace recruiters' decisions, supporting mutual learning and adaptation. As an experimental component of SMART, the Resume Parsing module is introduced, which leverages Large Language Models (LLMs) to extract information from resumes and structure it into a candidate profile, which serves as the knowledge base for subsequent candidate evaluation tasks.

Keywords: HR Intelligence · Multi-Agent AI Systems · Symbiotic AI · Large Language Models · Resume Parsing · Job Matching · BPM Process.

1 Introduction

The rapid evolution of the job market, characterized by increasing competition for highly qualified professionals and the growing complexity of organizational structures, is transforming the way companies manage recruitment and talent acquisition processes [16, 23]. In this context, Human Resources (HR) departments are required to identify, attract, and retain the most suitable candidates while simultaneously reducing hiring times, optimizing costs, ensuring compliance with regulatory requirements, and promoting diversity and inclusion [24].

Traditional recruitment processes often rely on manual screening activities and fragmented decision-making workflows, resulting in significant inefficiencies, extended time-to-hire, and potential biases in candidate evaluation [27]. Moreover, the increasing volume of applications and the emergence of new working models, such as remote and hybrid work environments, further challenge organizations in effectively matching candidate profiles with organizational needs [19]. Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and data analytics offer new opportunities to improve recruitment processes through the automation of candidate screening, intelligent matching mechanisms, predictive analytics, and decision-support systems [27, 19]. At the same time, the adoption of Explainable Artificial Intelligence (XAI) techniques has become essential to ensure transparency, accountability, and trustworthiness in AI-assisted hiring decisions, particularly in scenarios involving sensitive personal data and fairness considerations [3].

Alongside AI technologies, Business Process Management (BPM) and Case Management approaches provide organizations with the capability to model, monitor, optimize, and continuously improve recruitment workflows [26]. The integration of process-aware systems with AI-driven analytics enables the collection and exploitation of operational data generated throughout the recruitment lifecycle, creating a feedback loop that supports both process optimization and the continuous refinement of predictive models [4].

Within this context, the SMART (System for Matching And Ranking Talents) project aims to develop an innovative platform that combines no-code process technologies, BPM solutions, Machine Learning models, and Explainable AI techniques to support the entire recruitment and selection lifecycle. The platform is designed to automate candidate screening and matching activities, improve the quality and objectivity of recruitment decisions, reduce operational costs, and provide a transparent and inclusive candidate experience.

2 Related Works

The adoption of Artificial Intelligence (AI) has significantly transformed Human Resource Management (HRM), particularly talent acquisition and recruitment, by improving efficiency, reducing recruitment time, and supporting data-driven decision-making [20, 7]. AI-based solutions automate candidate sourcing, resume screening, assessment, and selection while enhancing workforce analytics and recruitment quality [7].

Recent studies have integrated Machine Learning (ML), Natural Language Processing (NLP), and semantic matching techniques to improve candidate ranking and skill extraction. Approaches based on SBERT, FAISS, TF-IDF, TextRank, and transformer architectures have demonstrated promising results in identifying suitable candidates through intelligent and context-aware matching [1, 15, 12, 21, 22, 10, 18, 9].

More recently, Generative AI and Large Language Models (LLMs) have further extended recruitment automation by supporting job description generation, candidate profiling, interview preparation, talent mapping, and conversational assistance [2, 8, 25, 11, 17]. These technologies improve candidate engagement while reducing the administrative workload of HR professionals.

Despite these advances, most existing solutions address individual recruitment tasks, such as resume screening, candidate ranking, explainability, or chatbot assistance, without providing an integrated recruitment ecosystem. To overcome this limitation, the proposed SMART platform combines intelligent candidate matching, predictive analytics, Explainable AI, process orchestration, and continuous recruitment monitoring within a unified framework.

3 SMART: System Workflow

This section presents the conceptual workflow of the SMART system, with particular reference to the core functionalities that operate on the individual stages of the recruitment process [13]. The workflow, illustrated in Figure 1, highlights an AI-based approach, in which a multi-agent system, powered by artificial intelligence techniques, operates in synergy with the BPM engine to support the entire selection cycle.
This design enables a reduction in evaluation time, an improvement in the accuracy and quality of candidate selection, and the digitalization and automation of activities traditionally managed manually. A further distinctive element of the proposed solution is its adaptability: through integration with no-code BPM systems, the architecture can be configured according to the specific recruitment processes of any organization, regardless of sector or organizational size.

Preparing. The preparation phase enables the requesting Hiring Manager to formalize a personnel request to the HR staff, expressing the need to hire a professional for a specific role according to defined criteria. Upon approval of the personnel request, the HR Talent Acquisition staff proceeds to create an Open Position, which outlines the ideal candidate profile, and launches the associated recruitment campaign. In the preparation phase, SMART's task is to support the HR staff in the creation of the Open Position, specifically through the following functionalities: (i) Collection of approved personnel requests from the corporate information system; (ii) Extraction of information contained in the personnel request, typically provided in a textual document, such as a form or a PDF file; (iii) Definition of the ideal candidate's duties, tasks, attitudes, qualifications, and skills, taking into account both organizational needs and current labor market

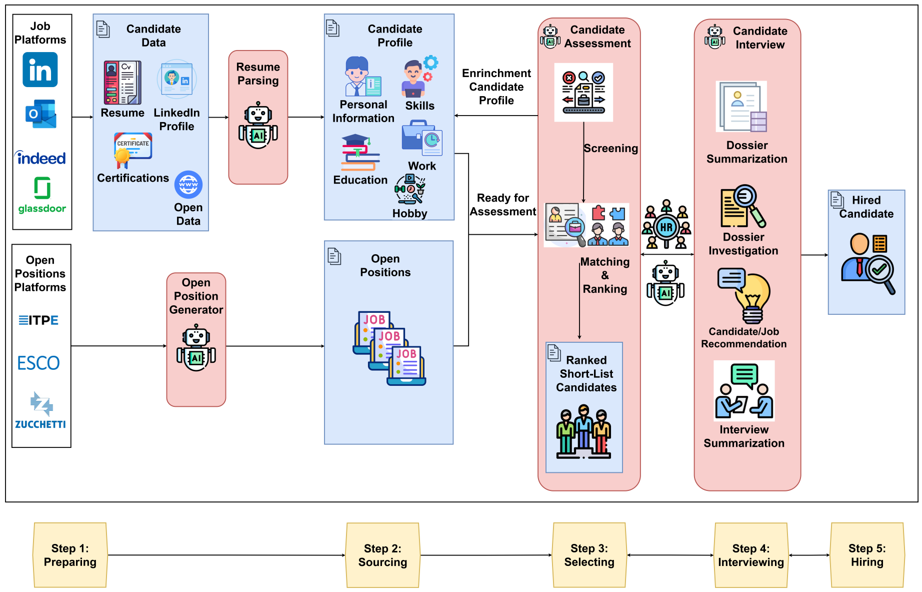

Fig. 1. SMART System Workflow

trends, leveraging European frameworks and standards such as ITPE (IT Professionalism Europe) or ESCO (European Skills, Competences, Qualifications and Occupations); (iv) Creation of the Open Position and the associated Job Description; (v) Definition of the Open Position catalog.

Sourcing. Following the launch of the recruitment campaign, the sourcing phase enables HR personnel to collect applications from multiple sources, including job platforms (e.g., LinkedIn, Indeed, and Glassdoor), corporate Applicant Tracking Systems (ATS), and email services used in initiatives such as Career Days and Employee Referral programs. In this phase, SMART is responsible for establishing communication with the aforementioned data sources, acquiring candidate applications and creating an individual candidate profile within the SMART talent pool. The candidate profile can be automatically extracted when an application is received, based on the information contained in the candidate's curriculum vitae. A SMART Resume Parsing system is capable of extracting raw information from a resume and structuring it into multiple information categories within the candidate profile.

Selecting and Interviewing. Once both the candidate profiles of individuals who have expressed interest in a given Open Position and the corresponding job profile are available, SMART can initiate the candidate-job matching process and support the construction of the recruitment funnel.
The evaluation process consists of three sequential phases: *Screening*, *Matching*, and *Ranking*. During the *Screening* phase, candidates are initially assessed

against the mandatory hiring requirements (e.g., education, experience, and location), allowing the system to identify eligible applicants and generate an initial shortlist. The *Matching* phase evaluates the shortlisted candidates by comparing their profiles with both mandatory (*Must Have*) and desirable (*Nice to Have*) requirements, producing a candidate–job fit score that quantifies the degree of alignment with the target position. Finally, the *Ranking* phase orders candidates according to their fit scores, supporting HR recruiters in the selection process.
The evaluation is performed twice during the recruitment lifecycle: an initial assessment based on the application data and a second assessment after screening and technical interviews. The additional information collected during interviews enriches candidate profiles and enables an updated matching score and ranking.
To further support recruiter decision-making, SMART provides AI-based services including candidate profile summarization, profile analysis, interview summarization, candidate recommendation from the talent pool, and job recommendation for alternative positions better aligned with the candidate's profile.

Hiring. The hiring decision remains under the responsibility of the HR Recruiter and Hiring Manager, while AI acts as a decision-support system within a Human-in-the-Loop (HITL) approach. Recruiters can validate, modify, or override AI-generated recommendations, providing feedback that continuously improves the underlying models and aligns them with organizational policies.

To foster trust and transparency, SMART integrates Explainable AI (XAI) techniques that provide interpretable explanations for candidate evaluations and ranking decisions. This enables recruiters to understand AI recommendations, deliver more informed and objective feedback to candidates, improve the candidate experience, and ensure compliance with regulatory frameworks such as the EU AI Act and GDPR.

4 SMART Case study: Resume Parsing

This section presents a first case study that can be integrated into SMART, focusing on Resume Parsing processes and the automatic construction of candidate profiles. The experiment consists of analyzing a candidate's resume and generating the corresponding candidate profile.
The proposed solution relies on the implementation of a Text Mining pipeline, composed of the following stages:

- Resume Text Extraction: reading and extraction text from a resume;
- Text Cleaning: preprocessing of the extracted text in order to make it suitable for parsing and mapping stages;
- Parsing and Mapping: analysis of the cleaned text and mapping of the extracted information in the correct categories of the provided data structure;
- Evaluation Framework: measuring the accuracy and reliability of parsing and mapping in relation to execution time.

Dataset. The experimentation was initiated through the construction of a dataset composed of 20 CVs related to IT roles, such as Software Developer, Data Scientist, and Software Architect, regardless of seniority level. The dataset was designed to represent the widest possible variety of CVs in terms of language, formatting, and length, in order to reflect the diversity of resumes collected during the candidate screening phase. CVs in both Italian and English were included, in PDF and DOCX formats, as well as Europass CVs with both horizontal and vertical layouts.
The documents were further classified according to their length, distinguishing between short CVs, consisting of a single page, medium CVs, ranging from 3 to 5 pages, and long CVs, consisting of 6 pages or more.
The dataset is composed by 10 short CVs, 5 medium CVs, and 5 long CVs.

Resume Text Extraction. Optical character recognition (OCR) is the process of converting an image having text in it into a machine-readable text format. The main reason of the development of this technology is that most scanned images are impossible to read using a text editor because they are formatted as matrices of pixels: there is no information about text or numbers because everything is a geometric form. On the other hand, documents having .txt format, for example, have a whole new behavior, because their content is encoded into Unicode format, allowing the machine to copy or indexing each character in the document. In between, there is PDF format, which can show one of the two structures, depending on the fact that it is a digital native PDF having encoded text, scanned PDF, that behaves like an image, or a mixed one where there is an underlying picture with invisible selectable text. SMART case study is designed to deal with different types of data, because CVs most common formats are PDF, followed by DOCX, txt and even jpgs or png. First models for OCR used template matching or feature analysis, but after machine learning explosion, models involving Support Vector Machines and Neural Networks were introduced. This marked an important point of evolution for further approaches like LSTMs and RNN. These are the basis for some of the libraries studied for the current case of study, involving LSTM-based, Transformer based and LLM-based frameworks. Among the different tools studied, there was the necessity to preserve a deterministic extraction of the raw text from the original sources of data, so it was preferred to avoid LLM based OCR extractors since they are completely probabilistic. For this reason, considering the various CV data types and the necessity to have a reproducible extraction, the main Python libraries analyzed are:

- DOCX2txt: this deals with DOCX data, which does not need a proper OCR, but a simply extraction of the text already natively contained in it. It is immediate to execute.
- PDFplumber: this deals with native PDF data that does not require performing OCR. It parses the PDF internal structure, extracting text objects, coordinates, font information and layout data directly from file's binary content. It is really fast and does not require any specific machine learning model.
- PaddleOCR [6]: this is the OCR library used for non-native PDFs. Its modular architecture implements a complete deep-learning OCR pipeline com-

posed of three stages: (i) Detection: a CNN-based detector identifies and localizes text regions within the document image; (ii) *Classification*: a lightweight CNN estimates the orientation of each text region and applies rotation correction when necessary; (iii) *Recognition*: a neural network combining convolutional and transformer-based components converts the detected text regions into machine-readable text.

More recent versions of the presented libraries have been studied and analyzed, like PaddleOCR-VL [5] that implements the integration with Vision Transformers as well as with Generative AI models, but considering the hardware and temporal execution limitations, it was considered an overkill approach for our case study.

Text Cleaning. The cleaning stage receives as input the raw text coming from the Extraction phase and uses some regex expressions to delete the decorator characters and symbols in order to give back a text that is clear, formatted and ready to be used for the mapping phase.

Parsing and Mapping. In this stage, the objective is to take the cleaned CV and map it to a template given as a guide to fill in the fields of the given structure with the right values extracted from the CV.
Table 1 shows the categories and their respective fields considered in the Resume Parsing process.
This procedure is demanded for a local Large Language Model (LLM) which has been deployed and tested for the task. The reason why a LLM based solution was chosen for accomplishing the mapping task is that, differently from keywords-based or deterministic approaches, generative AI semantic reasoning and sentences context analysis was used to better understand the extracted data and infer hidden or implicit information that is contained in the CV but not completely clear, like for example candidate job hopping or simple calculation like years of job experience. The given template for the mapping has been provided in JSON format, and the resulting best model for this purpose is Qwen 2.5 instruct with 14 Billion parameters. The point of strenght of this model is the capacity of being accurate to the JSON template provided as guide for the extraction, showing great results in extracting structured data from unstructured source. In particular, the model is running on a local server (CPU: Intel(R) Xeon(R) Silver 4208 CPU @ 2.10GHz, RAM: 96 GB, GPU: NVIDIA T4 16 GB) to preserve data privacy and to avoid that sensitive company information could reach external systems. The parameters of the local model used to run the experiments are: context window 31100 tokens, temperature 0, top p 0.1, top k 1 and repeat penalty of 1.0. The prompt given to the model follows the rules of Prompt Engineering, and consists of a system prompt and a user prompt. The system prompt defines the model's role, task, general constraints, and the expected JSON output format, while the user prompt contains, for each extraction category, task-specific instructions defining the required inference, together with the raw CV text.

Category	Fields
Personal Information	Full Name, Email, Linkedin Profile, Github Profile, Phone, Birth Date, City, Province, Country, Disability Flag, Driving License, Gender
Work Experience - Company	Company, Company Start Date, Company End Date, Current Company, Boomerang Employee, Experience Year Company
Work Experience - Project	Project, Client, Project Start Date, Project End Date, Project Role, Project Team Size, Project Description, Project Tasks, Languages, Frameworks, Tools
Work Experience - Summary	Job Hopping, Experience IT Year Total, Experience Year Role
Education	Institution, Start Date, End Date, Is Current, Degree Type, Course, Final Grade, Average Grade, Grade Honors, Thesis, Exam Name, Exam Grade, Exam Topics, Graduation Status, Is Working Student, Out of Course
Skills	Skill Name, Skill Type, Skill General Category
Languages	Language Name, Language Code, Is Native, Language Certified, Proficiency Level, Reading Level, Writing Level, Speaking Level
Certifications	Certification Name, Issuing Body, Issue Date, Expiry Date, Certification URL, Certification Level, Domain, Is Expired
Achievements	Achievement Title, Achievement Date, Achievement URL, Issuing Body, Achievement Type, Achievement Description
Hobbies	Hobby Name, Hobby Category

Table 1. Resume Parsing: category and fields

4.1 Evaluation Framework

The proposed evaluation framework assesses parsing efficiency measured by execution time, and parsing accuracy, measured in terms of the correctness of the information extracted in each category.
In first instance, the heterogeneous nature of the extracted information is considered, as it makes the adoption of a single evaluation metric impractical. The system-generated JSON schema contains fields characterised by different data types and varying levels of semantic complexity. Therefore, two fundamental dimensions are taken into account: (i) the data type, distinguishing among single values, lists, and free-text descriptions; and (ii) the degree of semantic interpretability, distinguishing between deterministic fields, which can be directly extracted without interpretation, and non-deterministic fields, which require inference, aggregation, or contextual understanding.
For deterministic fields, classical mathematical metrics are employed: Exact Match for strictly constrained fields, Levenshtein similarity for short textual fields where minor variations are acceptable, and the Jaccard index for compar-

ing set-based attributes.
For descriptive and huge information, an LLM-as-a-Judge is adopted, where a Large Language Model evaluates the semantic similarity between the parsed output and the ground truth. The prompt design follows established best practices [14], including role specification, evaluation criteria, evaluation instructions, evaluation score, and few-shot examples.
The model assigns a score in the range [0, 5], where 0 indicates no semantic correspondence and 5 indicates a perfect match. The score is subsequently normalised to [0, 1]. GPT-5 is used as the evaluation model.
This approach enables category-level evaluation rather than field-level comparison, significantly reducing annotation effort for complex descriptive categories. For privacy preservation, the model only accesses category-specific information and has no access to personally identifiable data.
The metrics associated with each category are defined in the table 3

Category	**Evaluation Method**
Personal Information	Average of field-level mathematical metrics
Work Experience - Company	Average of field-level mathematical metrics
Work Experience - Project	LLM-as-a-Judge
Work Experience - Summary	LLM-as-a-Judge
Education	Average of field-level mathematical metrics
Skills	LLM-as-a-Judge
Languages	LLM-as-a-Judge
Certifications	LLM-as-a-Judge
Achievements	LLM-as-a-Judge
Hobbies	LLM-as-a-Judge

Table 2. Resume Parsing: evaluation methods

The overall accuracy of a CV is computed as a weighted average of the scores obtained for each category:

$$Accuracy_{CV} = \frac{\sum_{i=1}^{n} w_i \cdot Score_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

where $Score_i$ denotes the score of category i and w_i denotes the weight assigned to category i. The introduction of weights allows assigning higher importance to categories that are generally more relevant in recruitment settings, such as personal information, work experience and education. Conversely, less relevant categories, such as hobbies, are assigned lower weights.

5 Results and Future Scope

Experiments were conducted on twenty resumes for which a manually annotated ground truth was constructed, corresponding to the desired candidate profile representation. The ground truth faithfully follows the original dataset structure and consists of 10 short CVs, 5 medium CVs, and 5 long CVs. The Resume Parsing results, reported in Table 3 are based on average values for both execution time and overall accuracy, as well as for the individual categories.

Resume	**Time**	**Acc**	**Pi**	**We**	**Edu**	**Sk**	**Lan**	**Cert**	**Ach**	**Hob**
Short CVs	1.22 min	0.83	1.00	0.70	0.90	0.75	0.90	0.90	0.70	0.80
Medium CVs	4.30 min	0.78	1.00	0.65	0.85	0.70	0.85	0.85	0.60	0.95
Long CVs	10.47 min	0.73	1.00	0.60	0.80	0.65	0.80	0.80	0.55	0.90

Table 3. Resume Parsing: evaluation results

The results show that the proposed approach achieves superior performance on short resumes, reaching an average accuracy of 83%. As the document length increases, a progressive degradation is observed in both execution time and extraction accuracy. The most significant drop is observed for long resumes, particularly those exceeding ten pages. From a category-level perspective, the system achieves very high performance on the Personal Information category and satisfactory results on Languages, Certifications, and Hobbies, as these fields are generally more structured and easier to extract. The most challenging categories are Work Experience and Achievements. This is due to several factors: Work Experience is inherently complex and often contains nested and unstructured information. Moreover, in real-world resumes, information is not always consistently aligned with the expected schema; for instance, junior profiles often include academic projects under the Projects section rather than the Education section, which introduces ambiguity and hallucination for the model. As the Resume Parsing system is currently a prototype within the SMART project, future work will focus on the adoption of more advanced LLMs, enhanced prompt engineering strategies aimed at reducing hallucinations, and an extension of the evaluation dataset. Moreover, a greater involvement of the human factor, HR recruiters, is expected in future iterations. An additional improvement will consist of introducing a natural language summary of the candidate profile, where extracted information is reformulated into human-readable text, providing a comprehensive "Wikipedia-style" overview of the candidate.

6 Conclusion

The SMART system aims to develop an HR Intelligence solution capable of optimizing the recruitment process by accelerating hiring activities and supporting the identification of the most suitable candidates for available job positions. By integrating Artificial Intelligence services, particularly HR Agents, together with a Business Process Management (BPM) engine, SMART provides several benefits to HR professionals, including the automatic and simultaneous analysis of

multiple resumes, the reduction of errors and biases in candidate evaluation, shorter screening and selection times—thereby reducing the risk of losing top talent—and the possibility of centralizing the entire recruitment process within a single innovative, digitalized, orchestrated, and automated platform.
Within this context, the proposed Resume Parsing service represents a highly innovative component that significantly reduces the time required to review resumes and provides structured information that is immediately available and easily accessible within the platform. More specifically, Resume Parsing module is responsible for generating the candidate profile, which constitutes the knowledge base for executing the Screening, Matching, and Ranking activities that form the core of the SMART platform.

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