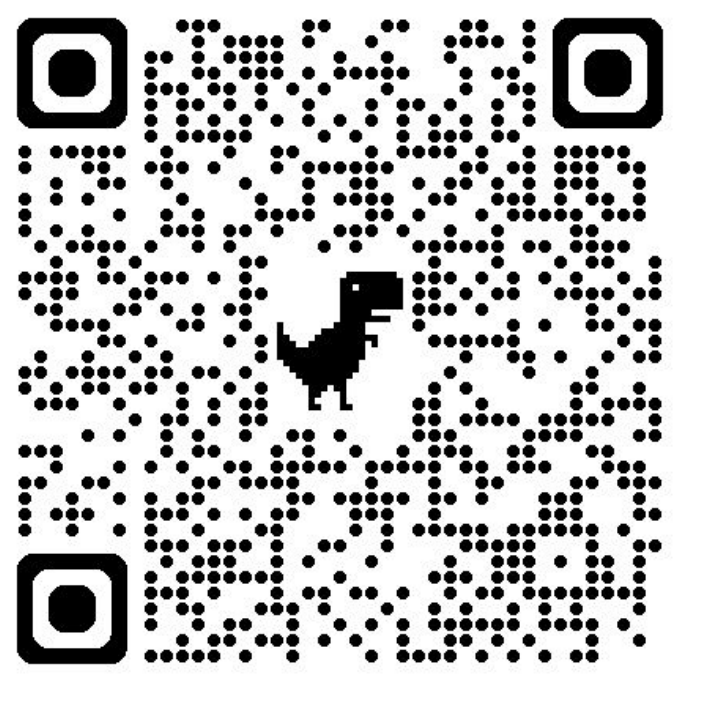




Skill extraction methods in **academic research** are frequently limited to **English job offers**, failing to capture the complexity of global recruitment. This study directly addresses this limitation. We evaluate multiple skill extraction methods across **six languages**, comparing **resumes** and **job offers** across diverse domains to build a more comprehensive, industry-relevant **framework**.

Summary

- Data:** 1,200 total documents across 6 languages: English, French, German, Italian, Spanish, and Portuguese.
- Split:** 100 job offers and 100 resumes per language in approximately 45 different professional domains.
- Human-in-the-Loop:** Resumes and job offers were manually annotated by HR specialists using the Docanno tool.
- HR Framework:** Skills were mapped using HRM literature and in-house expertise, utilizing the KSAO framework (Knowledge, Skills, Abilities, and Other attributes; Campion et al., 2011).

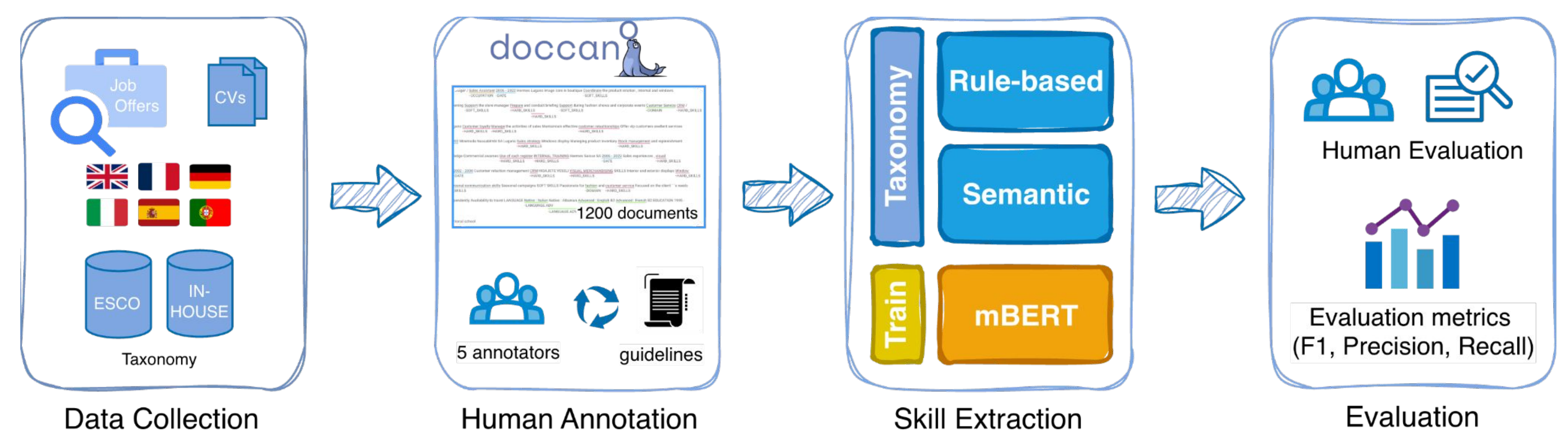
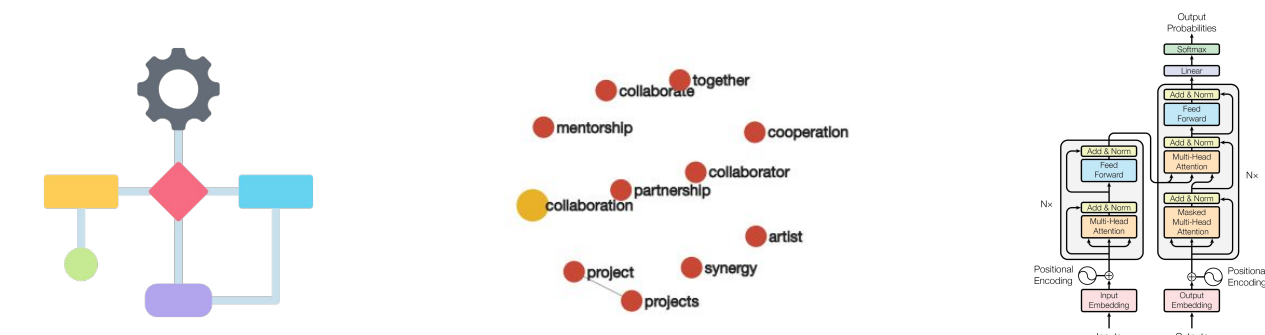


Figure 1. End-to-End Skill Extraction System

Multilingual Skill Extraction



Method	How?	Pros (+)	Cons (-)
Rule-based system	Strict matching using in-house (industry) and ESCO taxonomy	Fully transparent , taxonomy that is easy to update manually	Poor variability handling
Semantic (sentence embeddings)	Sentence embeddings to find closely related terms	Better generalization , extracted skills still traceable via the taxonomy	Cannot identify completely new concepts
Supervised mBERT	Fine-tuned, multilingual BERT-base model trained with manual annotations	Captures context across languages	"Black-box" model; harder to manipulate

Table 1. Skill Extraction Methods Comparison

Skill Extraction Examples

Job Offers (EN) - **Semantic (in-house)**

- An **analytical** approach to **problem solving** excellent **team working skills**
- An **analytical approach** to **problem solving** excellent team working skills

Resumes (EN) - **Rule-based (in-house)**

- From my experience, I learned and used different languages **PHP** **HTML** **CSS** **Javascript** **jQuery** **SQL** **Visual Basic** **Linux** **Bash** **FileMaker** **Script** **C**
- From my experience, I learned and used different **languages** **PHP** **HTML** **CSS** **Javascript** **jQuery** **SQL** **Visual Basic** **Linux** **Bash** **FileMaker** **Script** **C**

Key Takeaways

- mBERT wins on performance**
 - The fine-tuned model beats the rule-based and semantic systems by a wide margin, achieving exact **F1 Scores** up to **0.6**.
 - It avoids the expensive manual work to keep taxonomies updated.
- Occupations are easy, skills are hard**
 - Candidate's job titles are easy to find (with partial F1-scores up to 0.8).
 - Figuring out exactly **where** a **skill begins** and ends is still **very hard** for AI because people describe skills in different ways.
- Resumes are much harder than job ads**
 - Job ads are usually clean and organized.
 - Resumes** can be personal, and written in many **different styles**.
 - Our system found roughly 50% of the skills in English job offers, but that success rate dropped by half (to just 26.6%) on English resumes.

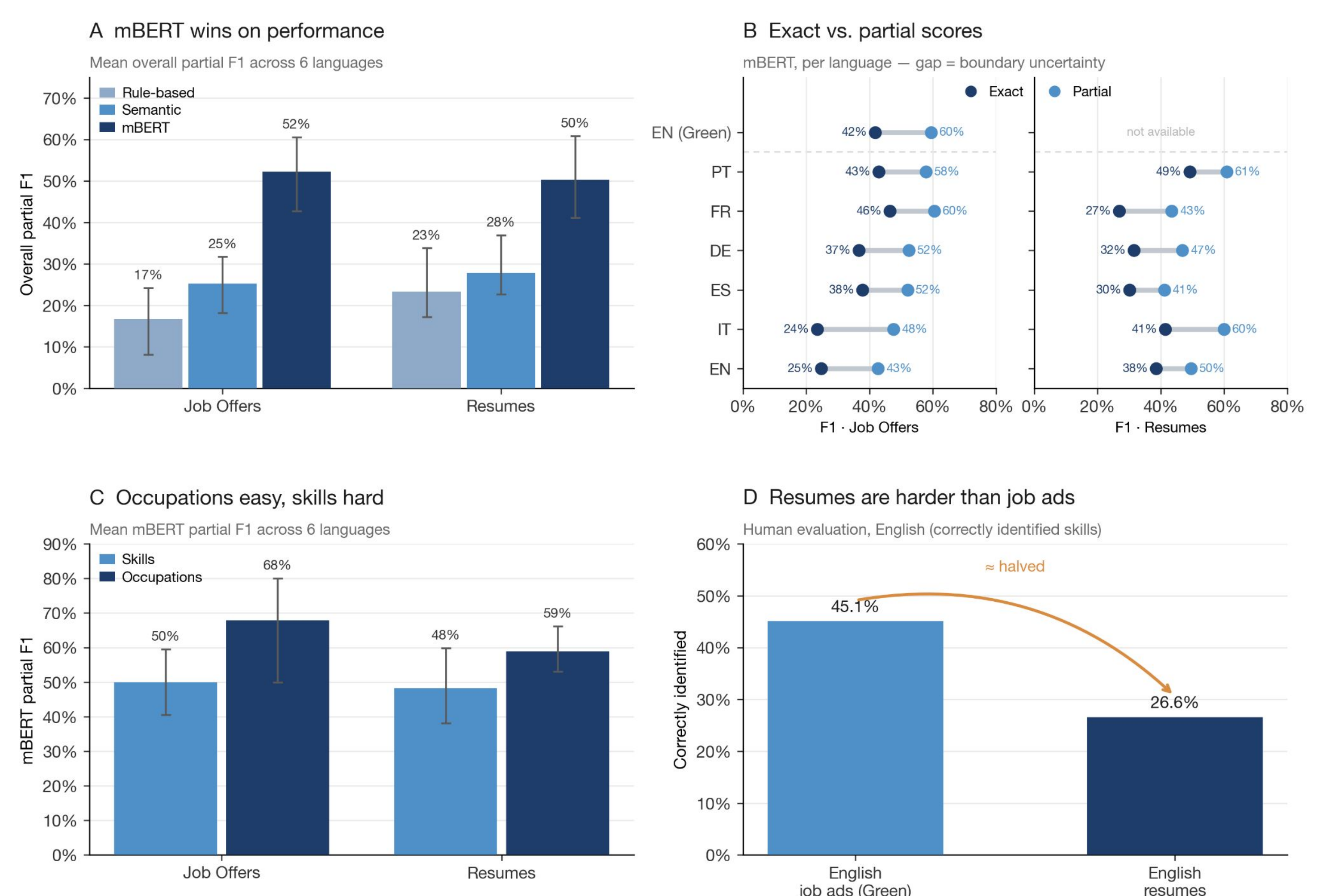


Figure 2. Skill Extraction Systems Results