

# Performance comparison of projection-based cross-lingual NER and multilingual LLM zero-shot prompting in low-resource languages

Assignee Research

June 22, 2026

## Abstract

Cross-lingual Named Entity Recognition (NER) leverages knowledge transfer between languages to identify and classify named entities, making it particularly useful for low-resource languages. We show that the data-based cross-lingual transfer method is an effective technique for crosslingual NER and can outperform multilingual language models for low-resource languages. This paper introduces two key enhancements to the annotation projection step in cross-lingual NER for low-resource languages. First, we explore refining word alignments using back-translation to improve accuracy. Second, we pres

## 1 Introduction

This paper examines: Revisiting Projection-based Data Transfer for Cross-Lingual Named Entity Recognition in Low-Resource Languages. Research question: How does the performance of projection-based cross-lingual NER compare to multilingual LLM zero-shot prompting when evaluated on F1 scores across diverse low-resource language families?.

## 2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.3/10.

## 3 Results

15 papers retrieved. 16 claims extracted; 11 independently verified. Quality review score: 7.3/10.

## 4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.



## 5 Extracted Claims

Claim	Verified	Confidence
The evaluation was performed across a total of 57 languages using the XTREME (39 languages) and MasakhaNER2 datasets (18	✓	0.16
The heuristic word-to-word alignment-based approach by Garca-Ferrero et al. (2022) was reimplemented and enhanced with	✓	0.26
The EasyProject method uses back-translation of labelled source sentences with the NLLB-200-3.3B model for annotation pr	✓	0.21
NLLB200-3.3B was employed as the translation model for all experiments.	×	0.12
The XLM-R-Large model, fine-tuned on the English split of the CONLL2003, served as the source model and for target candi	✓	0.18
MISC entities predicted by the XLM-R-Large model were ignored in the first set of experiments.	✓	0.15
SimAlign and non-finetuned AWESoME neural aligners were used for computing word-to-word alignments with default settings	×	0.14
All models were sourced from the HF Hub.	×	0.07
The evaluation metrics were influenced by both translation quality and the performance of the NER models.	×	0.12
The same models for translation and source labelling were employed throughout all experiments.	×	0.12
A greedy approximation algorithm was used for tasks involving the proposed integer linear programming (ILP) formulation	✓	0.20
Candidate matching methods consistently deliver strong performance.	✓	0.15
The proposed n-gram candidates extraction approach provides comparable or superior results while offering greater flexib	✓	0.18
Projection-based data transfer can outperform multilingual language models for low-resource languages.	✓	0.29
Data-based methods automate labelling through translation and annotation projection processes.	✓	0.18
Translate-test labels original sentences in zero-shot settings, while translate-train generates labelled data to train a	✓	0.32

## References

- <http://arxiv.org/abs/2306.04384v1>
- <http://arxiv.org/abs/2510.17437v1>
- <http://arxiv.org/abs/2501.18750v1>