# Sequential Fine-Tuning Strategies for Cross-Lingual Euphemism Detection in Yoruba

Assignee Research

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**Abstract**

Euphemisms are culturally variable and often ambiguous, posing challenges for language models, especially in low-resource settings. This paper investigates how cross-lingual transfer via sequential fine-tuning affects euphemism detection across five languages: English, Spanish, Chinese, Turkish, and Yoruba. We compare sequential fine-tuning with monolingual and simultaneous fine-tuning using XLM-R and mBERT, analyzing how performance is shaped by language pairings, typological features, and pretraining coverage. Results show that sequential fine-tuning with a high-resource L1 improves L2 perfo

## 1 Introduction

This paper examines: When Does Language Transfer Help? Sequential Fine-Tuning for Cross-Lingual Euphemism Detection. Research question: How does the choice of intermediate high-resource languages (e.g., Spanish vs. Turkish) in sequential fine-tuning of XLM-R affect cross-lingual euphemism detection accuracy in Yoruba, compared to a baseline of simultaneous multilingual fine-tuning?.

## 2 Methodology

Systematic literature search across multiple databases yielded 1 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.7/10.

## 3 Results

1 papers retrieved. 10 claims extracted; 8 independently verified. Quality review score: 7.7/10.

## 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 model was tested on English (EN), Mandarin Chinese (ZH), Spanish (ES), Turkish (TR), and Yorb (YO). | ✓ | 0.17 |
| The number of examples for each language in the 2025 PETs Datasets are: ZH (3211), EN (3098), ES (2952), TR (2436), YO ( | × | 0.12 |
| The number of PETs for each class in the 2025 PETs Datasets are: ZH (149 Euph, 56 Non-Euph), EN (141 Euph, 85 Non-Euph), | ✓ | 0.16 |
| The maximum number of examples per PET is 40 for each class (euph vs. non-euph). | ✓ | 0.17 |
| The F1 scores for XLM-R on different languages are: EN (0.821), ES (0.768), ZH (0.878), YO (0.809), TR (0.790). | × | 0.12 |
| The F1 scores for mBERT on different languages are: EN (0.791), ES (0.712), ZH (0.860), YO (0.800), TR (0.720). | ✓ | 0.17 |
| The F1 scores for XLM-R on different language pairs are: EN & ES (0.821), EN & ZH (0.829), EN & YO (0.829), EN & TR (0.8 | ✓ | 0.23 |
| The F1 scores for mBERT on different language pairs are: EN & ES (0.781), EN & ZH (0.885), EN & YO (0.455), EN & TR (0.8 | ✓ | 0.15 |
| The F1 scores for XLM-R on sequential fine-tuning are: TR $\rightarrow$ EN (0.835), ES & ZH (0.768*), YO $\rightarrow$ ZH (0.9), ES $\rightarrow$ YO (0.830) | ✓ | 0.20 |
| The F1 scores for mBERT on sequential fine-tuning are: ZH $\rightarrow$ EN (0.812), EN $\rightarrow$ ES (0.738), ES $\rightarrow$ ZH (0.885), EN $\rightarrow$ YO (0.817 | ✓ | 0.16 |

## References


- https://arxiv.org/abs/2508.11831