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LARGE LANGUAGE MODELS FOR SENTIMENT ANALYSIS TO DETECT SOCIAL CHALLENGES: A USE CASE WITH SOUTH AFRICAN LANGUAGES

Bloemfontein, South Africa
December 5, 2024

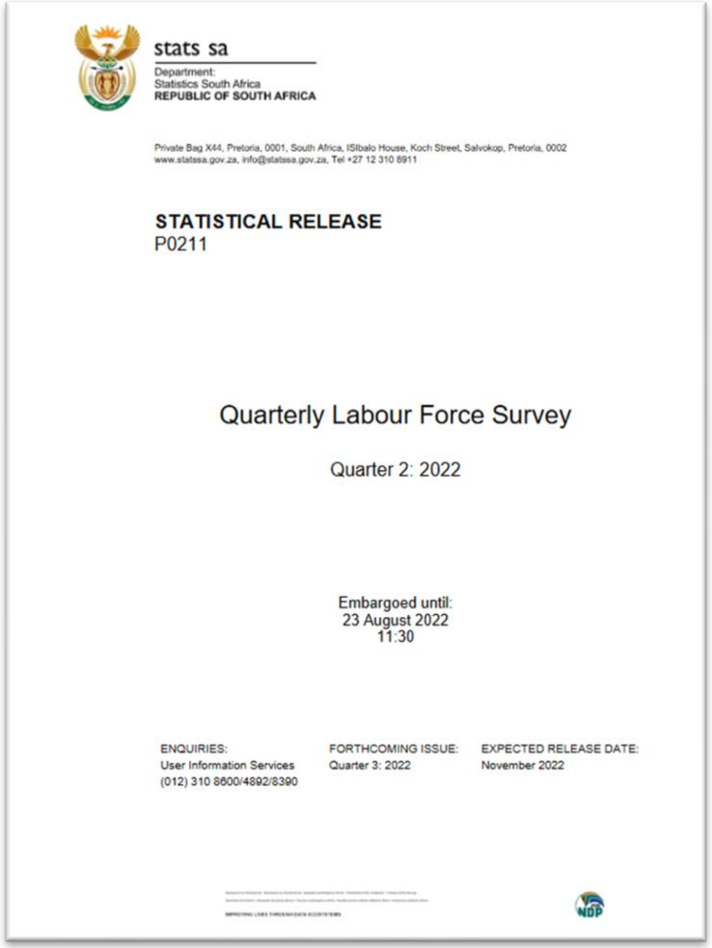
AGENDA

1

INTRODUCTION

MOTIVATION: Soc. Challenges in South Africa

UNIVERSITY OF JOHANNESBURG · HKA Hochschule Karlsruhe University of Applied Sciences · iu INTERNATIONAL UNIVERSITY OF APPLIED SCIENCES



stats sa
Department:
Statistics South Africa
REPUBLIC OF SOUTH AFRICA

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South Africa's Challenges of Realising her Socio-Economic Rights

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Abstract

Homelessness and poverty are huge challenges in South Africa. These social problems manifest themselves in poor housing. Inadequate and poor housing structures coupled with illegal land evasions as well as evictions have characterised the society since the Verwoerdian era and even during the new democracy. The ANC led government declared housing one of its constitutional mandate. Provision of the state's low cost housing is seen as a panacea to homelessness, inadequate housing and poverty. The fact that the democratic government declared housing a priority area, in itself gave birth to different perceptions in the minds of many people. Some people are occupying land illegally, which often municipalities will launch counter initiatives to evict them and take them to areas suitable for human settlement. Such an intervention is often fought fiercely by affected residents. There are people who believe that they can occupy any available vacant land because the Constitution of South Africa puts provision of adequate housing upon the state. This study used a qualitatative research methodology in gathering data in the affected areas of Limpopo Province, South Africa. Providing housing continues to be contested and the battle does not seem to have been won. Despite the challenges of the state, a framework has been established for the future.

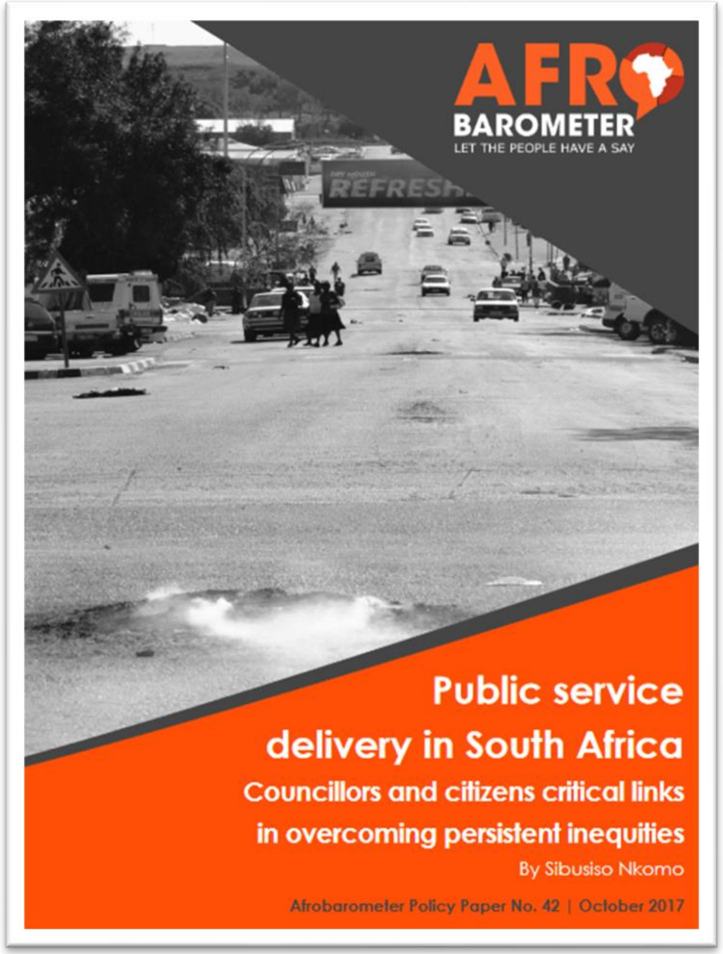
Keywords: Homelessness, apartheid, mekhukhu, democracy and South Africa

1. Introduction

South Africa as a developing country has a housing market that is skewed. The country experiences a huge housing backlog, which is often a distinct character in all developing countries. Developing countries attribute their inadequate housing and poor infrastructural development to underdevelopment. The Neo-Marxist theorists, most of whom may be regarded as proponents of the dependency theory in one form or another claimed that imperialism and colonialism have impeded progress throughout the Third World (Martinussen, 1997). This creates unequal relations between developed and developing countries. The unequal power relations between developed and developing countries has a negative impact on service provision in less developed countries like South Africa. In addition, South Africa was subjected to Verwoedian system which promoted migrant labour system. The migrant labour system created a need for housing in towns and cities. When more people travel to the cities in search of jobs, they were confronted with a critical housing shortage. They then came up with alternative means to construct cheaper housing structures. These people constructed dwellings from all varieties of materials which are frequently unsuitable for construction designs. For example, they use tins, pieces of plastic and low quality wood (Cloete, 1993). The use of unsuitable building materials to erect houses are equally a consequence of poverty and landlessness.

The Verwoedian government fought the shack dwellers with all its power. This created conflict between black people and the Verwoedian administration. The apartheid government resorted to evictions, removals and the enforcement of the Group Areas Act of 1950. The evictions affected the political landscape of the country. People's hopes rested in the violent conflicts which tragically characterised so many informal settlements since the mid-1980s (Smith, 1992). Evictions failed to resolve the problem of informal settlements as evictees continued to invade spaces near cities and forcefully sought to be part of the city settlements. The landless always resort to violent means to fortify their stay on invaded land. While some especially class issues were taken up, the campaigns, as a whole, were not overtly class based, on the common oppression of black people, especially African people under white rule (Marks, 1987). The unequal power relations between developed and developing countries further spiralled to unequal level of development

900



HIGH UNEMPLOYMENT RATE, POOR CONDITIONS IN HEALTHCARE FACILITIES, LACK OF EDUCATIONAL TOOLS, LACK OF WATER, ELECTRICITY & SANITATION

+ MORE CHALLENGES

Image and Text Sources: Quarterly Labour Force Survey – Quarter 2: 2022 (2022), Lorraine & Molapo (2014); Nkomo (2017).

MOTIVATION: Country Report & SDGs

+

JOB CREATION
ELIMINATION OF POVERTY
REDUCTION OF INEQUALITY
GROWING AN INCLUSIVE ECONOMY

74% CONVERGENCE

Image and Text Sources: Sustainable Development Goals: Country Report 2019 – South Africa; United Nations: Sustainable Development Goals: 17 Goals to Transform our World (2021).

MOTIVATION: Departments & SDGs

employment & labour
Department: Employment and Labour
REPUBLIC OF SOUTH AFRICA

small business development
Department: Small Business Development
REPUBLIC OF SOUTH AFRICA

education
Department of Education
REPUBLIC OF SOUTH AFRICA

transport
Department: Transport
REPUBLIC OF SOUTH AFRICA

correctional services
Department: Correctional Services
REPUBLIC OF SOUTH AFRICA

home affairs
Department: Home Affairs
REPUBLIC OF SOUTH AFRICA

agriculture, land reform & rural development
Department: Agriculture, Land Reform and Rural Development
REPUBLIC OF SOUTH AFRICA

water & sanitation
Department: Water and Sanitation
REPUBLIC OF SOUTH AFRICA

health
Department: Health
REPUBLIC OF SOUTH AFRICA

agriculture
Department: Agriculture
REPUBLIC OF SOUTH AFRICA

...

+

SUSTAINABLE DEVELOPMENT GOALS

MANDATE TO SUPPORT

Image and Text Sources: South African Government: National Departments (2022); United Nations: Sustainable Development Goals: 17 Goals to Transform our World (2021).

MOTIVATION: How to react quickly?

employment & labour
Department: Employment and Labour
REPUBLIC OF SOUTH AFRICA

small business development
Department: Small Business Development
REPUBLIC OF SOUTH AFRICA

education
Department of Education
REPUBLIC OF SOUTH AFRICA

transport
Department: Transport
REPUBLIC OF SOUTH AFRICA

correctional services
Department: Correctional Services
REPUBLIC OF SOUTH AFRICA

home affairs
Department: Home Affairs
REPUBLIC OF SOUTH AFRICA

agriculture, land reform & rural development
Department: Agriculture, Land Reform and Rural Development
REPUBLIC OF SOUTH AFRICA

water & sanitation
Department: Water and Sanitation
REPUBLIC OF SOUTH AFRICA

health
Department: Health
REPUBLIC OF SOUTH AFRICA

agriculture
Department: Agriculture
REPUBLIC OF SOUTH AFRICA

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SUSTAINABLE DEVELOPMENT GOALS

HOW CAN THE DEPARTMENTS BE INFORMED PROMPTLY ABOUT THE CURRENT SOCIAL ISSUES THAT AFFECT THEM, SO THAT THEY CAN THEN REACT QUICKLY?

?

Image and Text Sources: South African Government: National Departments (2022); United Nations: Sustainable Development Goals: 17 Goals to Transform our World (2021).

SENTIMENT ANALYSIS: English

automatically detecting a sentiment from textual information and then classifying the information into classes, e.g., classify tweets with government department related topics.

home affairs
Department:
Home Affairs
REPUBLIC OF SOUTH AFRICA

"The queue in home affairs at Wynberg is very slow one cannot get anything without waiting the service is bad."

twitter

negative

neutral

positive

SENTIMENT
ANALYSIS
CAN HELP

Image and Text Sources: South African Government: National Departments (2022); Mabokela & Schlippe (2022); Twitter (2022).

IDEA: LLMs for Sentiment Analysis

automatically detecting a sentiment from textual information and then classifying the information into classes, e.g., classify tweets with government department related topics.

home affairs
Department:
Home Affairs
REPUBLIC OF SOUTH AFRICA

"The queue in home affairs at Wynberg is very slow one cannot get anything without waiting the service is bad."

twitter

negative | neutral | positive

GPT-3.5
GPT-4.0

Dolly 2.0

PaLM 2

Llama 2

ZERO-SHOT CAPABILITIES:
EASY TO USE WITH PROMPTING

Image and Text Sources: South African Government: National Departments (2022); Mabokela & Schlippe (2022); Twitter (2022).

SENTIMENT ANALYSIS: Sepedi & Setswana

extracting subjective information from text such as mood,
e.g., classify tweets with government department related topics.

water & sanitation
Department: Water and Sanitation
REPUBLIC OF SOUTH AFRICA

Ke neng re lla ka mohlagase le makhura tsa go tura.

I was crying about expensive electricity and fuel

health
Department: Health
REPUBLIC OF SOUTH AFRICA

Puso ya rena ya ANC ga e re hlokomele ka tsa maphelo.

Our ANC government does not take care of our health

negative | neutral | positive

BANTU LANGUAGES ON X

Image and Text Sources: South African Government: National Departments (2022); Mabokela & Schlippe (2022).

EXPERIMENTAL SETUP

EXPERIMENTAL SETUP: System Pipeline

topic-specific search

+ data protection methods
+ text normalisation

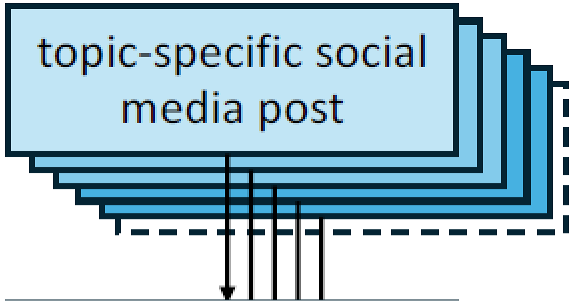
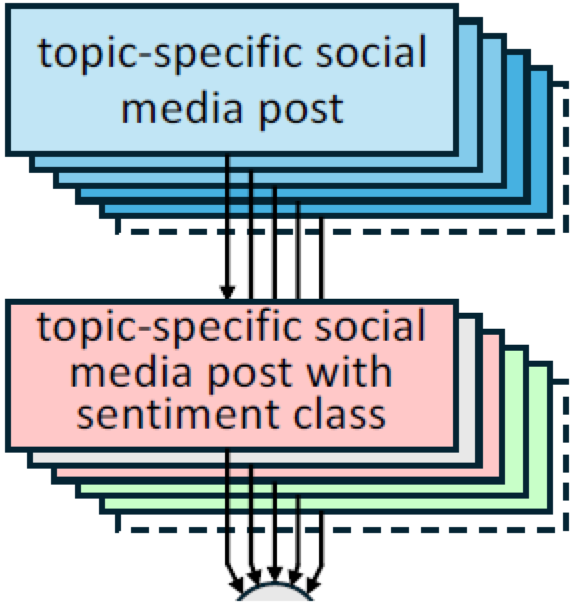


Image Source: Mabokela & Schlippe (2024).

EXPERIMENTAL SETUP: System Pipeline

topic-specific search



sentiment classification

negative
neutral
positive

Image Source: Mabokela & Schlippe (2024).

EXPERIMENTAL SETUP: System Pipeline

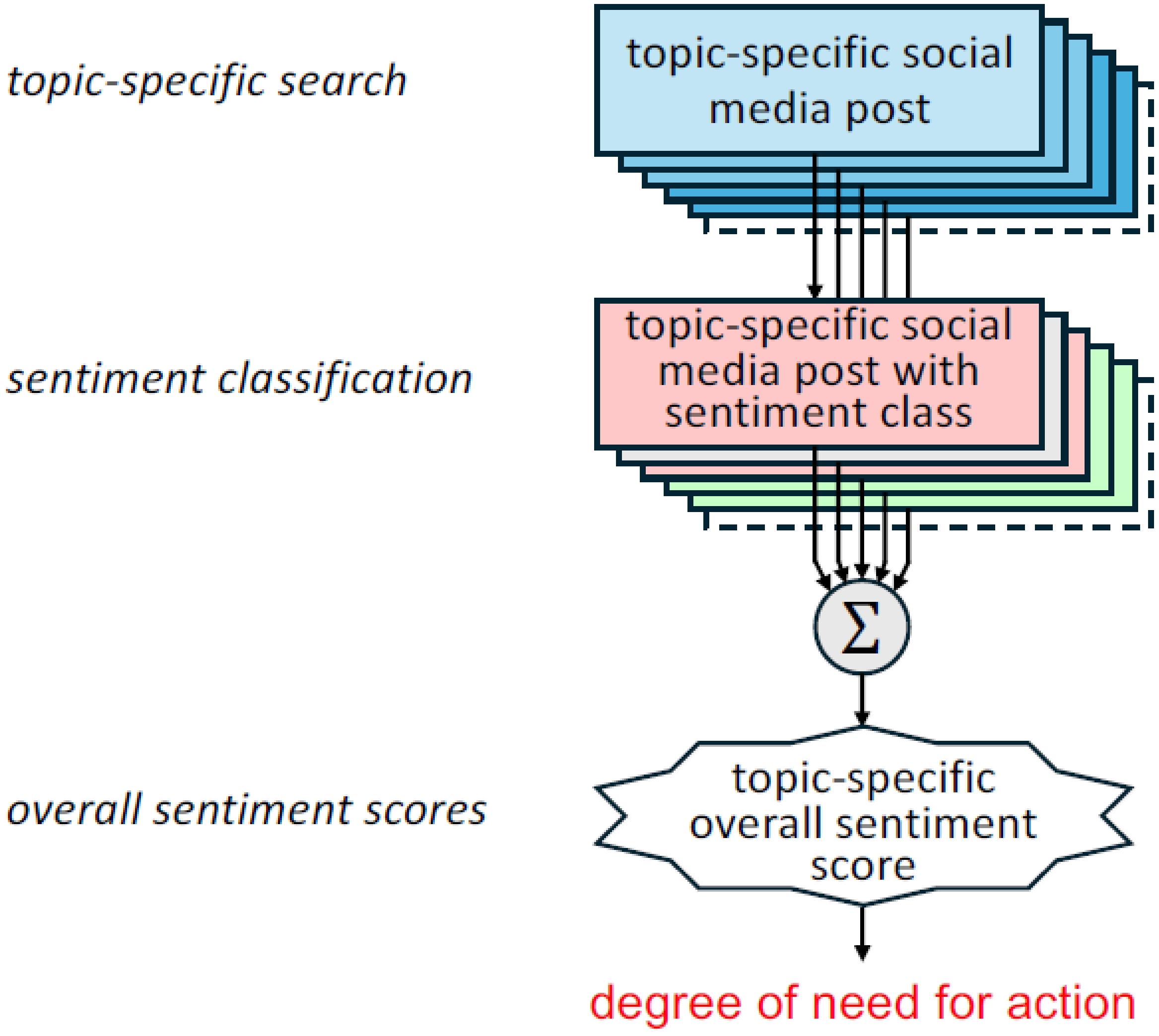


Image Source: Mabokela & Schlippe (2024).

EXPERIMENTAL SETUP: Prompting

Zero-Shot Prompting

Classify each tweet related to the topic '{topic}' as negative, neutral, or positive based on its content and context.

Instructions:

Read each tweet carefully.

Determine the sentiment expressed:

1. Output -1 for negative sentiment.
2. Output 0 for neutral sentiment.
3. Output 1 for positive sentiment.

Image Source: Mabokela & Schlippe (2024).

EXPERIMENTAL SETUP: Prompting

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Image Source: Mabokela & Schlippe (2024).

EXPERIMENTAL SETUP: Prompting

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Instructions:

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Determine the sentiment expressed:

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2. Output 0 for neutral sentiment.
3. Output 1 for positive sentiment.

CSV FORMAT

Image Source: Mabokela & Schlippe (2024).

EXPERIMENTAL SETUP: Prompting

Zero-Shot Prompting

Classify each tweet related to the topic '{topic}' as negative, neutral, or positive based on its content and context.

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Read each tweet carefully.
Determine the sentiment expressed:
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2. Output 0 for neutral sentiment.
3. Output 1 for positive sentiment.

ENGLISH PROMPT

1.0% BETTER F1 FOR SEPEDI
1.5% BETTER F1 FOR SETSWANA

Image Source: Mabokela & Schlippe (2024).

EXPERIMENTS AND RESULTS

LLMS' SENTIMENT CLASSIFICATION ERROR RATES ACROSS TOPICS AND LANGUAGES

	GPT-3.5	GPT-4	LLaMa 2	PaLM 2	Dolly 2
agriculture	11.2%	6.5%	10.9%	8.4%	11.9%
education	13.0%	8.4%	9.9%	8.9%	12.1%
employment	10.6%	6.7%	10.0%	6.5%	10.3%
health	13.5%	8.5%	11.0%	8.7%	12.5%
home affairs	12.4%	8.6%	12.7%	10.3%	12.1%
police service	12.9%	9.0%	12.6%	10.0%	11.0%
rural development	13.8%	6.3%	10.5%	12.6%	11.9%
sanitation	12.5%	7.0%	11.5%	8.9%	11.3%
small business	12.6%	7.5%	13.0%	10.4%	11.2%
transport	12.5%	10.9%	11.7%	8.8%	12.1%
English	12.8%	8.6%	11.9%	9.5%	12.0%
Sepedi	12.3%	7.0%	9.7%	8.0%	10.0%
Setswana	10.0%	7.3%	12.2%	8.8%	11.8%
Overall	12.5%	8.2%	11.5%	9.2%	11.6%

LOWER MEANS BETTER

Image Source: Mabokela & Schlippe (2024).

LLMS' SENTIMENT CLASSIFICATION ERROR RATES ACROSS TOPICS AND LANGUAGES

	GPT-3.5	GPT-4	LLaMa 2	PaLM 2	Dolly 2
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employment	10.6%	6.7%	10.0%	6.5%	10.3%
health	13.5%	8.5%	11.0%	8.7%	12.5%
home affairs	12.4%	8.6%	12.7%	10.3%	12.1%
police service	12.9%	9.0%	12.6%	10.0%	11.0%
rural development	13.8%	6.3%	10.5%	12.6%	11.9%
sanitation	12.5%	7.0%	11.5%	8.9%	11.3%
small business	12.6%	7.5%	13.0%	10.4%	11.2%
transport	12.5%	10.9%	11.7%	8.8%	12.1%
English	12.8%	8.6%	11.9%	9.5%	12.0%
Sepedi	12.3%	7.0%	9.7%	8.0%	10.0%
Setswana	10.0%	7.3%	12.2%	8.8%	11.8%
Overall	12.5%	8.2%	11.5%	9.2%	11.6%

GPT-3.5 GENERALLY EXHIBITS HIGHER SENTIMENT ERRORS

Image Source: Mabokela & Schlippe (2024).

LLMS' SENTIMENT CLASSIFICATION ERROR RATES ACROSS TOPICS AND LANGUAGES

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employment	10.6%	6.7%	10.0%	6.5%	10.3%
health	13.5%	8.5%	11.0%	8.7%	12.5%
home affairs	12.4%	8.6%	12.7%	10.3%	12.1%
police service	12.9%	9.0%	12.6%	10.0%	11.0%
rural development	13.8%	6.3%	10.5%	12.6%	11.9%
sanitation	12.5%	7.0%	11.5%	8.9%	11.3%
small business	12.6%	7.5%	13.0%	10.4%	11.2%
transport	12.5%	10.9%	11.7%	8.8%	12.1%
English	12.8%	8.6%	11.9%	9.5%	12.0%
Sepedi	12.3%	7.0%	9.7%	8.0%	10.0%
Setswana	10.0%	7.3%	12.2%	8.8%	11.8%
Overall	12.5%	8.2%	11.5%	9.2%	11.6%

GPT-4 TENDS TO SHOW THE LOWEST SENTIMENT ERRORS ACROSS ALL TOPICS (6.5%–10.9%)

Image Source: Mabokela & Schlippe (2024).

LLMS' SENTIMENT CLASSIFICATION ERROR RATES ACROSS TOPICS AND LANGUAGES

	GPT-3.5	GPT-4	LLaMa 2	PaLM 2	Dolly 2
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health	13.5%	8.5%	11.0%	8.7%	12.5%
home affairs	12.4%	8.6%	12.7%	10.3%	12.1%
police service	12.9%	9.0%	12.6%	10.0%	11.0%
rural development	13.8%	6.3%	10.5%	12.6%	11.9%
sanitation	12.5%	7.0%	11.5%	8.9%	11.3%
small business	12.6%	7.5%	13.0%	10.4%	11.2%
transport	12.5%	10.9%	11.7%	8.8%	12.1%
English	12.8%	8.6%	11.9%	9.5%	12.0%
Sepedi	12.3%	7.0%	9.7%	8.0%	10.0%
Setswana	10.0%	7.3%	12.2%	8.8%	11.8%
Overall	12.5%	8.2%	11.5%	9.2%	11.6%

LLAMA 2 (9.7%–13.0%) AND DOLLY 2 (10.0%–12.1%) ARE RELATIVELY SIMILAR, OFTEN BETWEEN GPT-3.5 (10.0%–13.8%) AND GPT-4 (6.3%–10.9%).

Image Source: Mabokela & Schlippe (2024).

LLMS' SENTIMENT CLASSIFICATION ERROR RATES ACROSS TOPICS AND LANGUAGES

	GPT-3.5	GPT-4	LLaMa 2	PaLM 2	Dolly 2
agriculture	11.2%	6.5%	10.9%	8.4%	11.9%
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health	13.5%	8.5%	11.0%	8.7%	12.5%
home affairs	12.4%	8.6%	12.7%	10.3%	12.1%
police service	12.9%	9.0%	12.6%	10.0%	11.0%
rural development	13.8%	6.3%	10.5%	12.6%	11.9%
sanitation	12.5%	7.0%	11.5%	8.9%	11.3%
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transport	12.5%	10.9%	11.7%	8.8%	12.1%
English	12.8%	8.6%	11.9%	9.5%	12.0%
Sepedi	12.3%	7.0%	9.7%	8.0%	10.0%
Setswana	10.0%	7.3%	12.2%	8.8%	11.8%
Overall	12.5%	8.2%	11.5%	9.2%	11.6%

PALM 2 (6.5%–12.6%) PROVIDES THE 2ND-BEST OVERALL PERFORMANCE.

Image Source: Mabokela & Schlippe (2024).

LLMS' SENTIMENT CLASSIFICATION ERROR RATES ACROSS TOPICS AND LANGUAGES

	GPT-3.5	GPT-4	LLaMa 2	PaLM 2	Dolly 2	Fused
agriculture	11.2%	6.5%	10.9%	8.4%	11.9%	0.3%
education	13.0%	8.4%	9.9%	8.9%	12.1%	0.5%
employment	10.6%	6.7%	10.0%	6.5%	10.3%	0.3%
health	13.5%	8.5%	11.0%	8.7%	12.5%	0.2%
home affairs	12.4%	8.6%	12.7%	10.3%	12.1%	0.4%
police service	12.9%	9.0%	12.6%	10.0%	11.0%	0.9%
rural development	13.8%	6.3%	10.5%	12.6%	11.9%	0.3%
sanitation	12.5%	7.0%	11.5%	8.9%	11.3%	0.6%
small business	12.6%	7.5%	13.0%	10.4%	11.2%	0.6%
transport	12.5%	10.9%	11.7%	8.8%	12.1%	0.6%
English	12.8%	8.6%	11.9%	9.5%	12.0%	0.4%
Sepedi	12.3%	7.0%	9.7%	8.0%	10.0%	0.7%
Setswana	10.0%	7.3%	12.2%	8.8%	11.8%	0.6%
Overall	12.5%	8.2%	11.5%	9.2%	11.6%	0.5%

MAJORITY VOTING IN THE FUSED SYSTEM LEADS TO LOWER ERROR RATES (0.2%-0.9%) FOR ALL LLMS

Image Source: Mabokela & Schlippe (2024).

LLMS' SENTIMENT CLASSIFICATION ERROR RATES ACROSS TOPICS AND LANGUAGES

	GPT-3.5	GPT-4	LLaMa 2	PaLM 2	Dolly 2	Fused
agriculture	11.2%	6.5%	10.9%	8.4%	11.9%	0.3%
education	13.0%	8.4%	9.9%	8.9%	12.1%	0.5%
employment	10.6%	6.7%	10.0%	6.5%	10.3%	0.3%
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transport	12.5%	10.9%	11.7%	8.8%	12.1%	0.6%
English	12.8%	8.6%	11.9%	9.5%	12.0%	0.4%
Sepedi	12.3%	7.0%	9.7%	8.0%	10.0%	0.7%
Setswana	10.0%	7.3%	12.2%	8.8%	11.8%	0.6%
Overall	12.5%	8.2%	11.5%	9.2%	11.6%	0.5%

ALL ANNOTATORS DISAGREE ON A SUBSET OF 1K POSTS IN 0.6% OF THE TWEETS

Image Source: Mabokela & Schlippe (2024).

LLMS' SENTIMENT CLASSIFICATION F1 SCORES ACROSS LANGUAGES

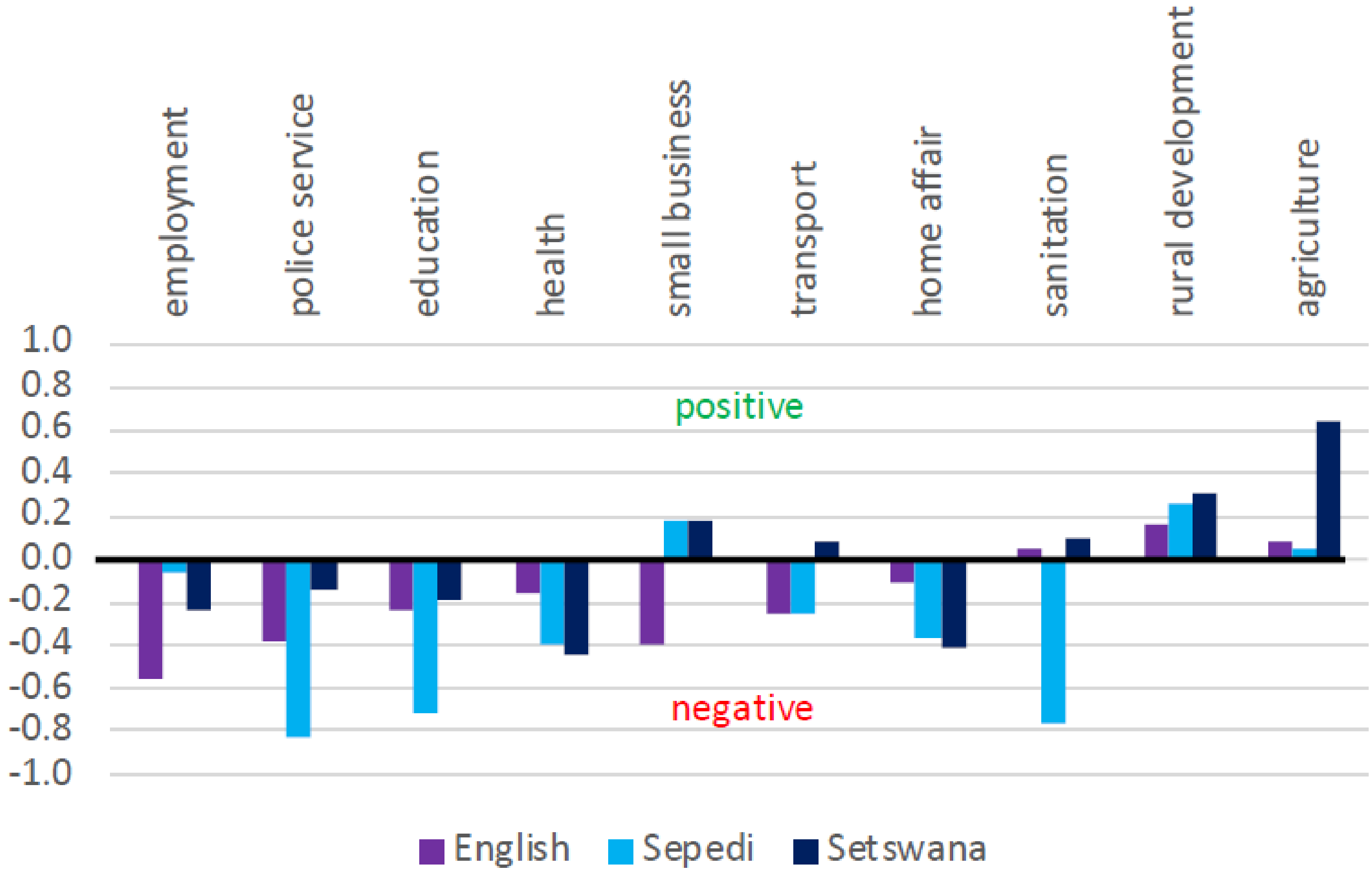
	GPT-3.5	GPT-4	LLaMa 2	PaLM 2	Dolly 2	Fused
English	91.0%	94.1%	91.6%	93.2%	91.5%	97.2%
Sepedi	91.9%	95.3%	93.6%	94.5%	93.3%	97.8%
Setswana	93.2%	95.3%	92.4%	94.3%	92.5%	97.4%
Overall	91.4%	94.4%	92.0%	93.6%	91.9%	97.5%

MABOKELA & SCHLIPPE (2022) WITH BERT:
ENGLISH: 86.0%
SEPEDI: 84.0%
SETSWANA: 82.7%

LLMS' PERFORM SIGNIFICANTLY BETTER THAN WHAT WAS REPORTED IN MABOKELA & SCHLIPPE (2022)

Image Source: Mabokela & Schlippe (2022).

OVERALL SENTIMENT SCORE



$$\frac{\#negative * (-1) + 0 * \#neutral * (+1) * \#positive}{\#allsentiments}$$

Image Sources: Mabokela & Schlippe (2022).

OVERALL SENTIMENT SCORE

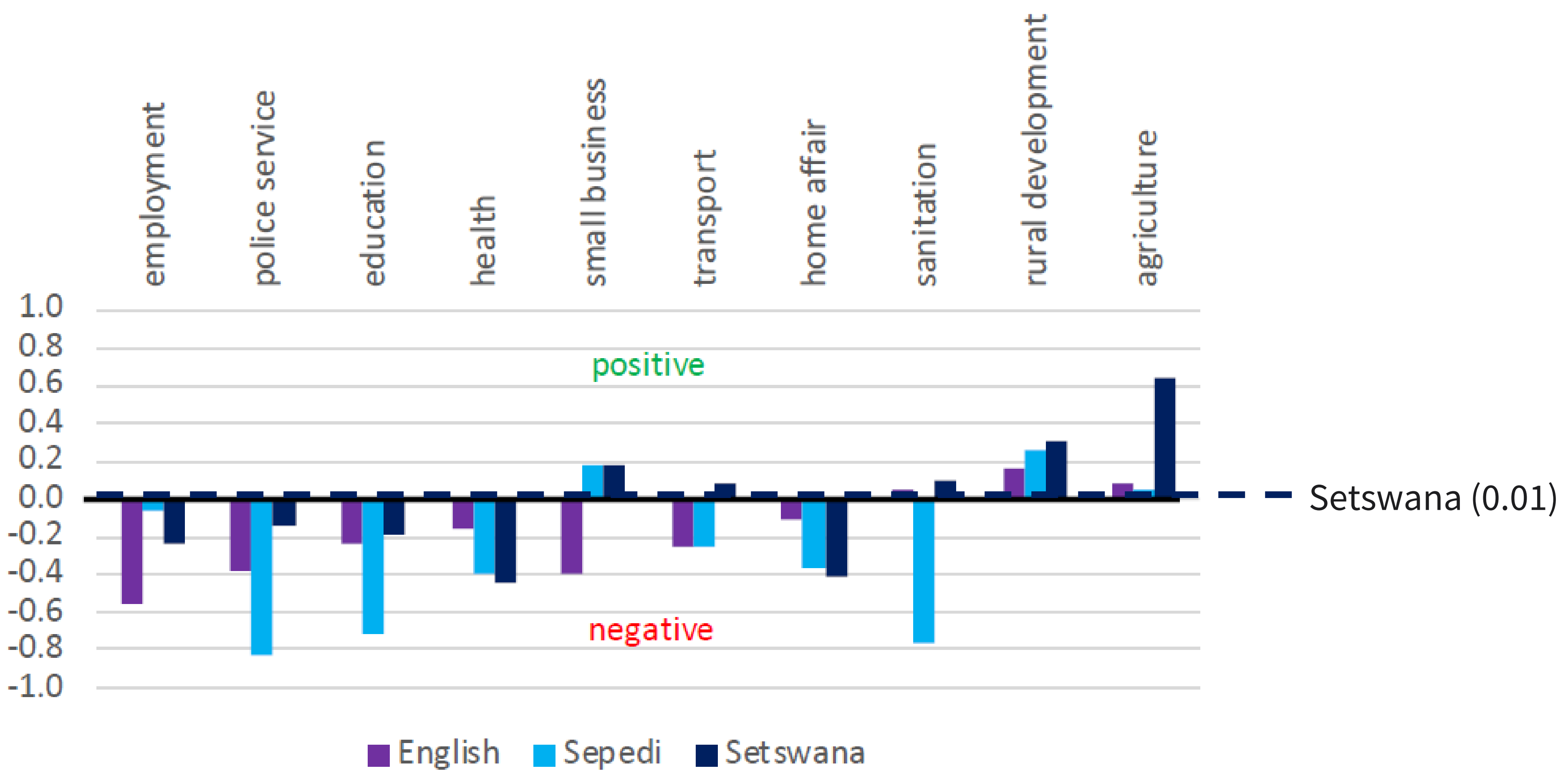


Image Sources: Mabokela & Schlippe (2022).

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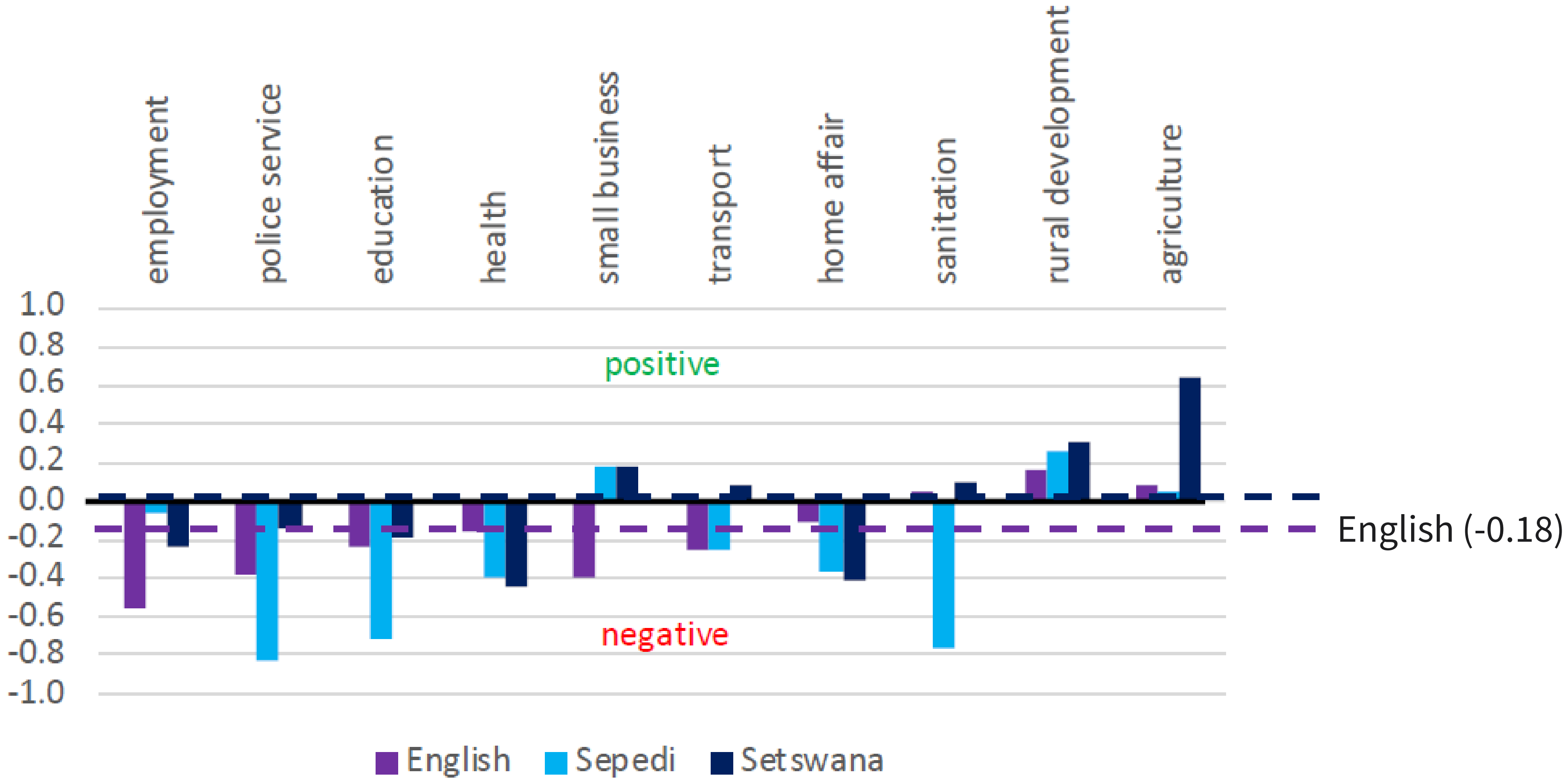

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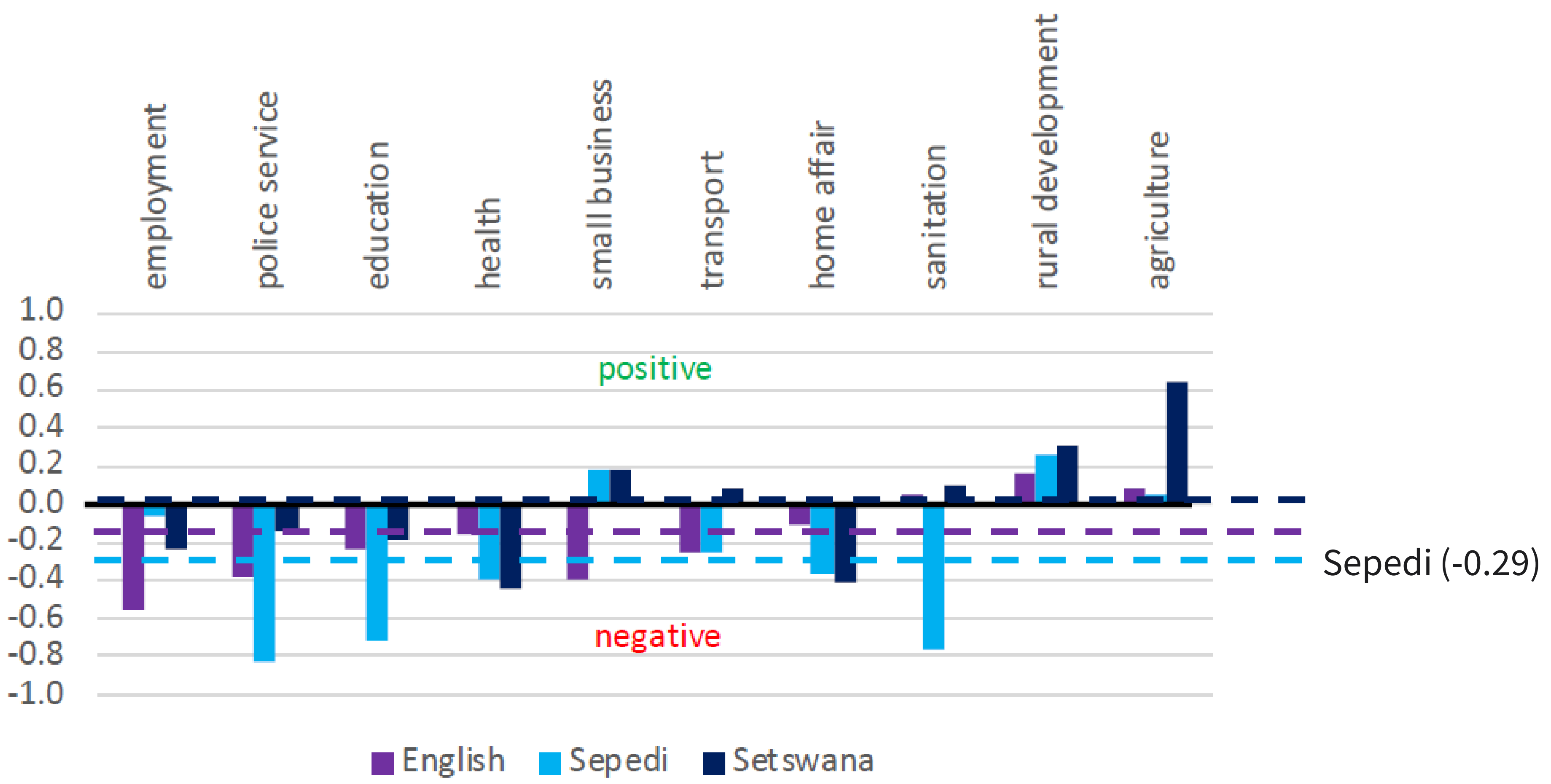

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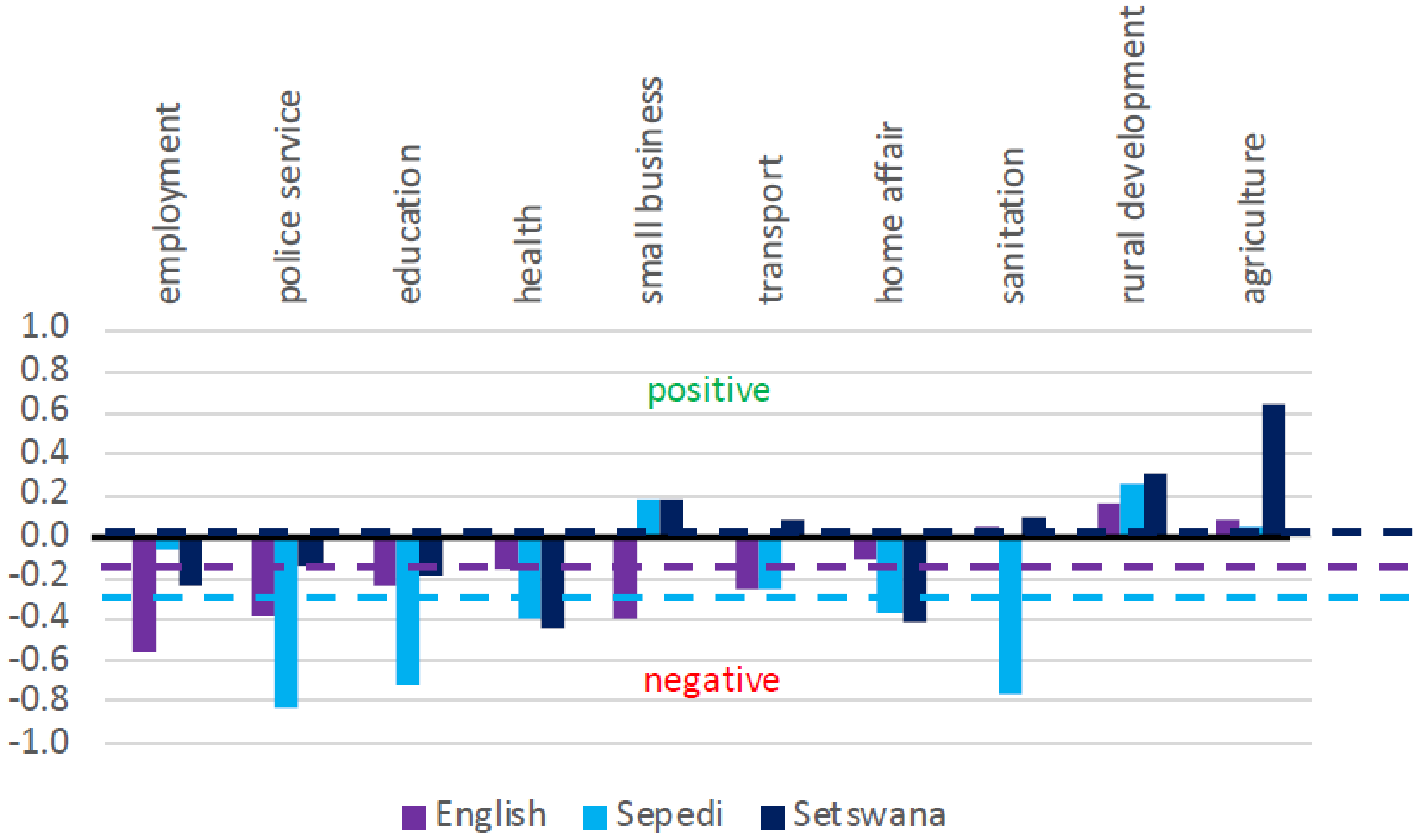

INFLUENCED BY CULTURAL, SOCIO-ECONOMIC, AND LINGUISTIC FACTORS

Image Sources: Mabokela & Schlippe (2022).

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- Investigate if more pronounced negative or positive sentiments between the languages for the same topics are due to linguistic and cultural differences or since the community is underserved
- Extension to other languages

THANK YOU

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Images

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