SAFARI: A Community-Engaged Approach and Dataset of Stereotype Resources in the Sub-Saharan African Context

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Abstract

Stereotype repositories are critical to assess generative AI model safety, but currently lack adequate global coverage. It is imperative to prioritize targeted expansion, strategically addressing existing deficits, over merely increasing data volume. This work introduces a multilingual stereotype resource covering four sub-Saharan African countries that are severely underrepresented in NLP resources: Ghana, Kenya, Nigeria, and South Africa. By utilizing socioculturally-situated, community-engaged methods, including telephonic surveys moderated in native languages, we establish a reproducible methodology that is sensitive to the region's complex linguistic diversity and traditional orality. By deliberately balancing the sample across diverse ethnic and demographic backgrounds, we ensure broad coverage, resulting in a dataset of 3,534 stereotypes in English and 3,206 stereotypes across 15 native languages. *Content Warning: This paper contains examples of stereotypes that may be offensive.*

1 Introduction

With rapid advances in generative AI (Achiam et al., 2023; Anil et al., 2023) and its widespread adoption (Chatterji et al., 2025), there is growing focus on ensuring its utility and safety across the globe (Jernite et al., 2022; Parrish et al., 2023). Recent work has investigated model safety failures in different parts of the world (Birhane et al., 2021; Ganguli et al., 2022; Kirk et al., 2022), with a particular focus on compiling lists of stereotypes to assess how these models propagate stereotypes about communities worldwide (Mitchell et al., 2025; Parrish et al., 2022). These lists are sourced through different methods, including LLM-based generation (Jha et al., 2023), large-scale surveys (Dev et al., 2023), or annotation studies (Bhutani et al., 2024). However, significant gaps persist in global coverage, along with concerns about the data collection approaches themselves (Smart et al., 2024).

Nowhere are these gaps more evident than in sub-Saharan Africa, where NLP datasets have historically lacked adequate coverage and quality (Kreutzer et al., 2022; Nekoto et al., 2020; Ousidhoum et al., 2025). While recent efforts such as the Masakhane project,[1] and Africa-focused research on tasks like machine translation (Adelani et al., 2022), hate speech detection (Muhammad et al., 2025), cultural understanding (Ahmad et al., 2024), and language understanding in general (Ojo et al., 2025) have made significant leaps, there remains a lack of stereotype resources that capture the local cultural knowledge from the region.

Overcoming this deficiency effectively requires a participatory and tailored approach to adapt large language models (LLMs) to the nuanced sociocultural realities of the continent (Adebara and Abdul-Mageed, 2022; DeWitt Prat et al., 2024; Rashid et al., 2025; Oluka, 2024). Crucially, a truly participatory framework must also adapt the conventional Western data collection methods, as these are often incompatible with local contexts due to technological barriers like limited internet access, costly mobile data, and poor keyboard support for local languages (Ade-Ibijola and Okonkwo, 2023; Travaly and Muvunyi, 2020).

To address these critical gaps in both data and methodology, this paper introduces the sub-**S**aharan **AF**rican **A**ssociations about **R**egionally-salient **I**dentities (SAFARI) dataset, developed through an in-depth community-engaged process (see Figure 1). SAFARI utilizes telephonic surveys, conducted by local partners, to honor the region's rich oral traditions (Tchindjang et al., 2008)—a direct counterpoint to prevailing traditional data collection paradigms in the West. Spanning four major sub-Saharan African countries with high populations (from the top-15)—Ghana, Kenya, Nigeria, and South Africa—the dataset contains stereo-

[1] https://www.masakhane.io/

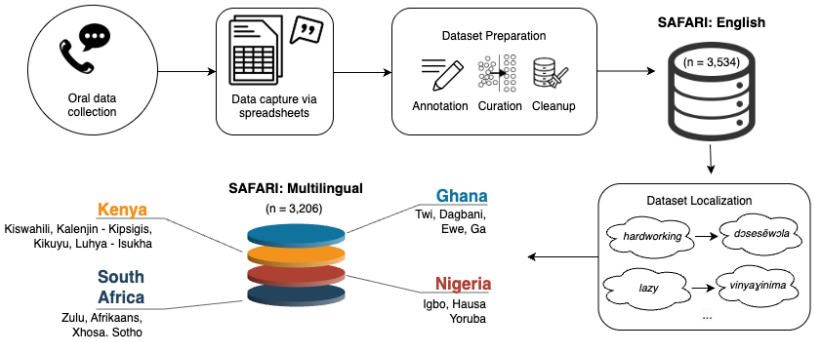

Figure 1: Our community-engaged methodology towards curating the multilingual SAFARI dataset, comprising 3,206 stereotypes across four countries and 15 languages. See Appendix D (Table 7) for the language distribution.

types in 15 languages (in addition to English), each enriched with crucial local context such as perceived offensiveness and regional prevalence. We present SAFARI not only as a vital resource for building more equitable language models, but also as a methodological blueprint for more participatory data collection in AI.

2 Data Collection Methodology

Recent work in the space of LLM Safety has demonstrated the importance of growing stereotype resources in community-engaged ways (Davani et al., 2025). These approaches introduce into consideration a vast majority of sensitive identities and prevalent stereotypes that are otherwise not safeguarded against, leading to major safety and representational failures in generative AI. Our work builds upon some of these notable community- and people-centered approaches such as HESEIA in Latin America by Ivetta et al. (2025), SPICE in India by Dev et al. (2023), and SHADES by Mitchell et al. (2025) globally. However, we find that these approaches fall short in the highly diverse, multiethnic, multilingual, as well as extremely underserved context of our target African countries – where oral expression captures a lot more value and nuance. We create a methodology that specifically caters to the languages and countries of interest.

2.1 Survey Mode

Given the linguistic complexity of African languages, which includes rich morphology and sophisticated tonal variations (Imam et al., 2025; Jerro, 2018), relying on written surveys (Dev et al., 2023) or interactive written tools (Ivetta et al., 2025), risked missing crucial nuances in oral communication. Our methodology, therefore, is grounded in a dual linguistic strategy (Oyekunle, 2025), wherein community knowledge is first gathered orally in the indigenous language and then recorded bilingually in the dataset, using both English and the native language. We leverage telephonic surveys with localized moderation in the respondent's preferred language, which allows a balance between broad reach and the ability to capture nuanced, authentic, and orally-expressed data.

2.2 Local Partnerships

This research study was conducted in collaboration with two organizations located in and operating within the countries of focus.[2] The recruitment of participants across communities was a collaborative effort between both of these organizations, with one of them also serving as the moderator for telephonic surveys in an array of languages commonly used in the countries of interest, and also preparing and translating the data. These partnerships were vital to ensure that local perspectives drive the salient questions of participant selection, demographic distribution, data quality, localization of survey questions, and more. Our study recruited 410 participants, at least 100 from each country. We employed a controlled quota sampling strategy based on the distribution of major ethnic groups within each country. We initiated the study with a screener to record demographic data and ensure adherence to the desired participant distribution.

2.3 Interview Protocol

We obtained informed consent from all participants and disclosed the monetary compensation amount (See details in Appendix A) beforehand. During the telephonic interview, participants were

[2]We redact the names of the organizations to maintain anonymity of all collaborators. We will make the names explicit in our camera-ready version.

asked to share 10 to 15 prevalent stereotypes from their country (with a limit of three stereotypes per identity term to encourage diversity). They were also asked about the degree of offensiveness of the stereotype, its prevalence, and the axis of identity that the stereotype is about. These additional features will help identify the impact model failures can have when they perpetuate certain stereotypes. The survey in its entirety is shared in Appendix B.

2.4 Data Capture & Localization

Moderators were selected based on their fluency in the native languages as reported by the participants in the screener, in order to conduct interviews in each participant's preferred language. Despite this, we had to adopt a two-step approach that first captured the stereotypes in English which were then translated back to local languages by professional linguists. This was necessary because direct real-time transcription was often impractical (except for Swahili) due to linguistic and technical constraints. Moderators, while fluent speakers, often lacked the necessary written proficiency in native languages, a situation rooted in well-documented systemic challenges (Appiah and Ardila, 2021; Bamgboşe, 2000; Matavire, 2024; Mncwango and Sithole, 2017). Furthermore, standard electronic keyboards lack the specialized symbols and characters required for many languages from sub-Saharan Africa (Chimkono et al., 2021), and the unique phonetic signs inherent in these languages' orthographies cannot be represented by Roman characters.

Except for Swahili in Kenya, the moderators initially recorded all responses in written English, where applicable. To recover the original linguistic nuance, professional linguists were subsequently hired to translate these standardized English responses back into the participant's native language, or to translate Swahili entries to English for completeness of our English dataset.

2.5 Data Preparation & Annotation

Following the initial data capture, the recorded stereotype statements were broken down and annotated into three key components as outlined in Table 1. A single identity term can relate to multiple axes. For instance, the term 'Hausa women' involves both the gender and ethnicity axes. Furthermore, identity axes can overlap. For example, the term 'Northerners' may indicate both a regional identity and a cluster of specific ethnicities associated with the Northern region of Ghana. Participants also provide additional social context about the stereotypes they share. They do so by rating each stereotype they shared on two perceived parameters: *Offensiveness*, rated on a 5-point scale (1 = Not Offensive; 5 = Extremely Offensive), and *Prevalence*, rated on a 4-point scale (1 = Rarely Used; 4 = Extremely Prevalent) (Appendix C).

Name	Description	Example
Identity Term	A word or phrase used to describe a significant aspect of a personal or social identity.	Nigerians, Policemen, Zulu Women
Stereotype Attribute	The word associated with or used to describe the mentioned identity term.	Violent, Lazy, Ritualists, Liar
Identity Axis	Broader categories that group related identity terms.	Ethnicity, Race, Gender

Table 1: Key terms used in the SAFARI dataset

3 The SAFARI Dataset

We introduce SAFARI (sub-**S**aharan **AF**rican **A**ssociations about **R**egionally-salient **I**dentities), a dataset comprising 3,534 stereotypes in English and 3,206 stereotypes in 15 native languages (listed in Table 7), collected from 410 participants across four countries. Specifically, it contains 1,919 stereotypes tied to ethnic groups in Ghana, Kenya, Nigeria and South Africa, and 382 stereotypes related to regions or states within these countries, thereby highlighting its granular, local focus.

3.1 Dataset Characteristics

Diverse Participant Base The study cohort features a largely balanced gender distribution, with 52.4% Male (n=215), 46.8% Female (n=192), and 0.7% Non-Binary (n=3) participants. Age representation in the cohort spanned a wide range, from individuals aged 18-24 up to the 65+ age group. We particularly aimed for diversity across ethnicity, tribes, and linguistic identity, as these elements form the core social fabric of our target countries. Our study cohort collectively represents 56 ethnic groups and speaks over 120 unique languages (with the majority of participants being at least bilingual).

Overlap with Other Resources Our dataset has minimal overlap with common stereotype resources, all of which exhibit geographical limitations: StereoSet (Nadeem et al., 2021), SPICE (Dev et al., 2023) and HESEIA (Ivetta et al., 2025) are limited to the perspectives from the USA, India, and Latin America, respectively. While SeeGULL Multilingual (Bhutani et al., 2024) covers Swahili (Kenya), the Swahili subset of SAFARI only shares

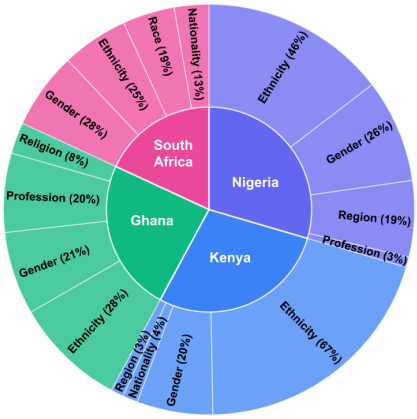

Figure 2: Country-wise distribution of dominant identity axes in the SAFARI stereotype dataset

four common identity terms with it; in fact, we introduce 168 new, unique identity terms, not previously covered. StereoSet does include seven African nationality-based identities, but the stereotypes were derived solely from US-based participants. In contrast, our resource features stereotypes shared by participants *from* Sub-Saharan Africa.

Prominent Identity Axes: While ethnicity and gender remain the most dominant identity axes of stereotypes across the entire dataset, country-specific distributions reveal unique patterns, as depicted in Figure 2. In Nigeria, region is the third-most dominant identity axis after ethnicity and gender. Ghana's focus shifts to profession as its third major axis. The pattern in South Africa is unique, with race and nationality placing highly due to the country's distinct racial diversity.

3.2 Analysis and Evaluations

Common Stereotype Attributes: 128 stereotypes mentioning 'black magic,' 'witchcraft,' 'ritualistic', or 'juju' are found in the dataset, with 82.8% from Ghana and Kenya combined. These stereotypes primarily target ethnic groups, particularly the Ewe (Ghana), and the Kisii and Kamba (Kenya). 152 stereotypes related to financial status or display of wealth (with mentions of 'rich', 'love money', 'show off wealth', 'extravagant') emerge. 61.8% of these relate to ethnic groups, primarily associated with the Kikuyu (Kenya) and Igbo (Nigeria). Of the 327 profession-related stereotypes in the dataset, 74.6% emerge from Ghana, and most of these carry a negative connotation, targeting professions like police ('corrupt', 'take bribes'), politicians ('liars', 'corrupt'), and nurses ('unprofessional', 'disresepctful'). Out of the 1,034 gender-related stereotypes, 57.9% target women, and the remaining 42.1% target men.

Country	Gemini 2.5	GPT-4O
Kenya (Swahili)	23.58 (19.81)	19.08 (16.77)
Ghana (Akan)	9.16 (9.55)	4.54 (7.81)
Nigeria (Hausa)	8.83 (17.04)	8.07 (9.3)
South Africa (Zulu)	5.68 (5.22)	2.46 (3.23)

Table 2: Rate of stereotype endorsement by industry leading models.

Prevalence of Stereotypes in Generative AI: We test whether AI models endorse stereotypes from SAFARI in English or in languages from each of the four countries. We create and employ human translators to carefully translate NLI based test templates (Dev et al., 2020) and evaluate the tendency to stereotype in generation (Jha et al., 2023) by Gemini 2.5 (Comanici et al., 2025) and GPT-4O (OpenAI et al., 2024). Table 2 underscores that not only do models stereotype in respective commonly used languages of each country, but also in English to a very similar extent. This, in turn, highlights the need to account for stereotypes from underrepresented regions of the world to prevent potentially harmful generations.

4 Discussion and Future Work

We present the SAFARI dataset, that fills a critical data gap for AI safety in sub-Saharan Africa, while also contributing a novel methodology for culturally situated data collection in NLP. Through a locally-situated and community-engaged approach, we collected over 3K stereotypes in English as well as 15 native languages from Ghana, Kenya, Nigeria, and South Africa. This dataset enables us to reveal previously undetected instances of stereotypes propagated by leading generative AI models, validating the urgent need for this work. Furthermore, our use of moderated, in-language telephonic interviews represents a novel data collection approach for NLP. This method provides a practical blueprint for navigating the complex techno-linguistic challenges prevalent in many global regions, effectively bypassing obstacles like low digital access and languages with orthographies unsupported by standard keyboards. Our work underscores the necessity of expanding data collection to more languages and global regions, while also accounting for such local realities, and we strongly encourage future research to build upon this foundation.

Limitations

Our work was aimed at improving the coverage of stereotype resources across languages prevalent in four countries in sub-Saharan Africa. While we attempt to carefully increase this coverage alongside maintaining demographic diversity of participants, we were limited by both our methodology and resources available to us. In particular, telephonic interviews allowed us to orally gather and record stereotypes, and thus reduce barriers related to writing, but we were still limited by connectivity issues. In particular, we may have failed to reach participants in remote areas who lack phones or reliable phone connectivity. For collecting perspectives from these specific, harder-to-reach groups, in-person surveys may be a better-suited methodology.

Our localization approach, described in Section 2, required a multi-step translation process, that may risk the loss of some subtle linguistic nuance and context as presented in the original spoken form. This focus on language preservation is critical, particularly because moderators observed that a stereotype's offensiveness was often diluted when translated into English, suggesting a valuable future research avenue concerning the loss of semantic and emotional nuance during cross-lingual transfer.

Further, our resource, while foundational for studying stereotypes in the sub-Saharan African context, is not exhaustive. It covers the major ethnic groups and native languages within our target countries, but omits many other ethnicities and languages due to limited sample size and resource constraints. Future research must expand upon this foundation to achieve comprehensive coverage of the numerous additional countries, languages, and ethnicities in sub-Saharan Africa. We recommend cross-referencing the findings from this expanded work with established traditional stereotype literature from the region (Fakunmoju and Bammeke, 2017; Harneit-Seivers, 2007; Lawson et al., 2015; Naituli and King'oro, 2018; Tewolde, 2024).

Ethical Considerations

Our research further highlights the high degree of linguistic complexity in sub-Saharan Africa. While our resource provides a significant subset of stereotypes towards ascertaining safety of generative models, they are in no way to be used to declare a model free of biases. For that, a lot more work and thought would be needed, including a much more exhaustive data collection. We also note that the recorded stereotypes should be only used for purposes of model evaluation and improvement as detailed in our Data Card (Appendix A) in order to prevent misuse.

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Appendix

A Dataset Details

A.1 Data

The complete dataset and its accompanying data card are provided in the supplementary materials, within the "SAFARI" folder. These resources will be released publicly through a GitHub link upon paper decision.

The dataset is structured into two tabs:

- The first tab, 'safari_english', contains 3,534 rows (excluding the header), each containing a stereotype and its corresponding annotations
- The second tab, 'safari_multilingual', includes 3,206 rows (excluding the header), each containing a stereotype from the multilingual subset of the dataset, covering 15 languages (following the distribution outlined in Table 7), along with corresponding annotations and the English counterpart for cross-reference.

The difference in the number of English (n=3,534) and multilingual (n=3,206) stereotypes is attributable to two factors: first, English-language interviews were not translated into a native language when English was the participant's preferred language; and second, in cases of less commonly spoken languages with limited linguist availability.

A.2 Dataset Sample

Below is a sample data entry to illustrate key parameters recorded in the dataset:

- **Country:** Kenya
- **Stereotype Sentence (English):** *Mijikenda people are lazy*
- **Identity Term (English):** Mijikendas
- **Stereotype Attribute (English):** Lazy
- **Identity Axis (English):** Ethnicity
- **Offensiveness (1-5):** 3 - Slightly offensive
- **Prevalence (1-4):** 3 - Commonly used
- **Target Language:** Kiswahili
- **Identity Term (Kiwsahili):** Wamijikenda
- **Stereotype Attribute (Kiswahili):** Wavivu

A more detailed version is presented in the data card provided in the supplementary materials.

A.3 Data Cleaning Steps

To clean the survey responses for precise counting and reporting, the following manual edits were applied:

- Instances of "woman" and "women" were standardized to "women". Similarly, "Igbos" and "Igbo" (when referring to the people) were standardized to "Igbos", and other identity terms were treated similarly.
- Language names were standardized (e.g. 'Kiswahili' and 'Swahili' updated to 'Kiswahili'; 'isiZulu' and 'Zulu' updated to 'isiZulu', and so on).
- Other minor cleaning steps included correcting spelling errors and trimming extra white space within cells to prepare the data for usage and analysis.

A.4 Review, Consent & Compensation

Dataset and data collection were reviewed by an internal, organizational, proprietary review board.

Prior to the study, informed consent was obtained from all participants, who confirmed they met the minimum age requirement (18+). The consent form explicitly stated their right to withdraw from the study at any time without penalty, and the option to decline any specific question asked to them. They were briefed on the study's purpose and the procedures for data retention, storage, and protection. In addition to the written consent form, the moderators ensured participants received these details verbally.

The dataset does not contain any Personally Identifiable Information (PII). All PII was scrubbed during collection. Unique, non-traceable identifiers (e.g., GH001, KE002, etc) were used solely for analysis and data counting purposes, but these cannot be used to trace or link back to the participating individuals.

For completing the telephonic survey, each participant was compensated in a fair and legally compliant manner with an amount that exceeded minimum local wage requirements. The incentive amount was mentioned in the screener shared beforehand. Duration of the telephonic interview was capped at 15 minutes per participant.

The two local organizations we partnered with were compensated either according to a pre-established Statement of Work (SOW) for services provided (in one case), or through a mutual agreement on the amount and deliverables (in the other). We will name both organizations and co-authors in the camera-ready version.

B Interview Design and Methodology

Section 1: Screener Demographic Questions

The following information was collected during the initial screening phase:

1. Country of Data Collection
2. Gender Identity
3. Age
4. Hometown / Region
5. Religion
6. Ethnicity / Tribe
7. Sub-Tribe (where applicable)
8. Language(s) Spoken
   (a) Primary (Native)
   (b) Secondary
   (c) Other
9. Highest Level of Completed Education
10. Occupation

Section 2: Stereotype Elicitation Questions

Respondents were asked to share at most 10-15 stereotypes known in their society and community (as much as they could comfortably list within the limit of a 15-minute interview).

1. **Question:** What stereotypes do you know in your society and community?
   (a) **Recording:** The stereotype was recorded, first as a sentence, and then broken down to an *identity term* and an *attribute term* (e.g., Nigerians, rich).
   (b) **Axis of Identity:** The identity term's axis was classified (e.g., gender, tribe, religion, language, race, age, profession).
   (c) **Offensiveness Rating:** Respondents were asked to rate the stereotype's offensiveness using a 1-5 scale (presented in Appendix C, Table 3)
   (d) **Prevalence Rating (Optional):** Respondents rated the stereotype's prevalence using a 1-4 scale (presented in Appendix C, Table 4)
2. **English Translation:** The closest English translation was provided by the moderator post-interview, not during the collection process.

Collection Guidelines

To ensure diversity of responses, the following limits were applied per participant:

- Not more than 3 stereotypes about any single identity term (e.g., Hausas).
- Not more than 5 stereotypes relating to any single identity axis (e.g., profession).

C Rating Scales

Participants were asked to rate the offensiveness of each shared stereotype on a 5-point scale (Table 3), and its prevalence on a 4-point scale (Table 4).

Rating (Score)	Definition
1	Not Offensive at all
2	Unsure
3	Slightly Offensive
4	Somewhat Offensive
5	Extremely Offensive

Table 3: Offensiveness Rating Scale

Rating (Score)	Definition
1	Rarely Used
2	Occasionally Used
3	Commonly Used
4	Extremely Prevalent/Popular

Table 4: Prevalence Rating Scale

D Data Details

D.1 Participant Diversity

The total number of stereotypes and participants per country is described in Table 5. The participants of our data collection effort were diverse along different demographic axes. Table 6 describes the gender distribution of our participants per country.

Country	Number of Stereotypes	Number of Respondents
Ghana	1037	101
Kenya	892	108
Nigeria	954	100
South Africa	651	101
Total	**3534**	**410**

Table 5: Data Collection Summary by Country

D.2 Language Distribution

The language distribution of the multilingual stereotype dataset is shown in Figure 3 and Table 7.

D.3 Demographics by Country

The country-wise distribution of ethnic groups and tribes in the study cohort is presented in Table 8.

E AI Usage in Writing

We used a conversational AI tool to help lightly rephrase or shorten a few sentences, find alternate terms, and table formatting.

Country	Gender	Percentage (%)
Ghana	Male	54%
	Female	46%
Kenya	Female	50%
	Male	49%
	Non-binary	1%
Nigeria	Male	58%
	Female	42%
South Africa	Female	50%
	Male	49%
	Non-binary	2%

Table 6: Gender Distribution of Study Cohort by Country

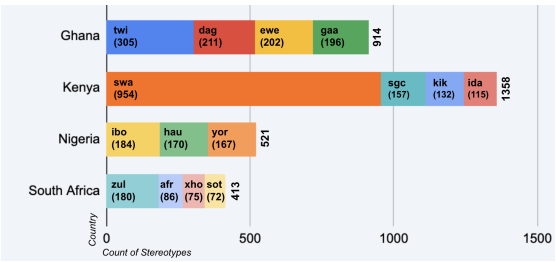

Figure 3: The SAFARI dataset represents 15 native languages from 4 countries. Table 7 provides the expanded ISO codes.

Country	Language	ISO 639-3	Count
Kenya	Kiswahili	swa	954
	Kalenjin (Kipsigis)	sgc	157
	Kikuyu	kik	132
	Luhya (Isukha)	ida	115
	Kenya Total		**1358**
Ghana	Twi	twi	305
	Dagbani	dag	211
	Ewe	ewe	202
	Ga	gaa	196
	Ghana Total		**914**
Nigeria	Igbo	ibo	184
	Hausa	hau	170
	Yoruba	yor	167
	Nigeria Total		**521**
South Africa	Zulu	zul	180
	Afrikaans	afr	86
	Xhosa	xho	75
	Sotho	sot	72
	South Africa Total		**413**
		Grand Total	**3206**

Table 7: Distribution of Multilingual Stereotypes by Country and Language

Country	Ethnic Group	Percentage (%)
Ghana	Akan	31%
	Ewe	20%
	Ga-Adangbe	19%
	Mole-Dagbani	17%
	Others	14%
Kenya	Kikuyu	18%
	Kalenjin	15%
	Luhya	14%
	Kamba	12%
	Kisii	10%
	Luo	10%
	Mijikenda	10%
	Others	11%
Nigeria	Hausa	22%
	Igbo	20%
	Yoruba	20%
	Others	28%
	Ijaw	10%
South Africa	Zulu	25%
	Xhosa	12%
	Afrikaans	10%
	Tswana	10%
	Pedi	9%
	Basotho	7%
	Others	26%

Table 8: Distribution of Study Cohort by Ethnic Group (Tribe) and Country