Machine Learning Analysis of Radio Data to Uncover Community Perceptions on the Ebola Outbreak in Uganda

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Radio is vital for people, especially in rural areas, to share their concerns through interactive talk shows. Understanding public perceptions of pandemics is crucial because they influence people's attitudes and health-seeking behaviors. This study used machine learning to analyze English and Luganda radio broadcast data to understand public perceptions and perspectives on the Ebola outbreak in Uganda. Our findings revealed three main speaker categories: media personalities, community guests and listeners, and government officials. The government made the most significant effort to educate the public about the Ebola outbreak. The analysis showed that the community was hesitant to use Ebola vaccines, believing that they had not been tested on other populations where the Ebola virus had originated. The community was also concerned about the effects of the lockdown measures imposed during the COVID-19 pandemic. The analysis of the radio broadcast data revealed differences in the timing and content of the conversations between male and female speakers. These experiences can inform population-specific policies for handling ongoing and future pandemics.

CCS Concepts: • **Computing methodologies** → **Machine learning approaches**; **Speech recognition;**

Additional Key Words and Phrases: Speech recognition, Ebola outbreak, perceptions, radio data

This work was funded by the Makerere University Data Science Research Training to Strengthen Evidence-Based Health Innovation, Intervention and Policy (MakDARTA) - 1U2RTW012116-01.
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ACM 2834-5533/2024/09-ART38
https://doi.org/10.1145/3685697

ACM Reference Format:
Joyce Nakatumba-Nabende, Jonathan Mukiibi, Tobius Saul Bateesa, Sudi Murindanyi, Andrew Katumba, and Chodrine Mutebi. 2024. Machine Learning Analysis of Radio Data to Uncover Community Perceptions on the Ebola Outbreak in Uganda. *ACM J. Comput. Sustain. Soc.* 2, 3, Article 38 (September 2024), 28 pages.
https://doi.org/10.1145/3685697

1 Introduction

Radio continues to be a reliable and affordable way to access and share information in regions with limited internet connectivity. Radio platforms are crucial for people, especially in rural areas, to air their concerns through interactive radio talk shows that encourage community call-ins. A total of over 55% of the Ugandan population use radio as their source of information compared to 7.3% who use the Internet [52]. Moreover, 59.6% of them own a radio compared to 13.9% television ownership, 5.1% fixed phone, and 3.8% computer ownership [52]. This presents radio as a more inclusive alternative communication medium in Uganda. Uganda has over 218 licensed radio stations [13], which provides a valuable opportunity for citizens to have their voices heard and to discuss issues that could lead to better government policies.

In many African countries, community radios were created to serve local communities, where people interacted closely [27]. However, with the rise of new **information and communication technologies** (**ICTs**), the concept of “community” has been redefined, and people in disparate locations can communicate with each other via community radios as if they were in the same physical place [36]. This is achieved through emerging digital media platforms employed in radio talk shows and discussion programs that have gained popularity across numerous community-based radio stations in Africa [35, 36]. Moreover, using ICTs has dramatically transformed how radio programs are researched, prepared, broadcasted, received, monitored, and evaluated [15].

Community radio stations frequently host radio talk shows, during which the public can utilize ICTs to communicate their viewpoints and opinions on various community-related matters. In such programs, radio communication is interactive, and information is shared between hosts, presenters, and community listeners. This bi-directional communication occurs via **Short Messaging Services** (**SMS**) and call-in programs [15]. Radio talk shows often feature first-hand accounts of incidents and information as reported by citizens. Radio has proven a highly effective medium for reaching communities, particularly during health emergencies and crises. For example, a recent study showed that radio was the most popular way for over 85% of the population to get information about an Ebola outbreak in Sierra Leone [5, 50]. During a disease outbreak and crisis, monitoring the various community radio broadcasts is necessary for policymakers and government agencies to obtain citizen concerns and input for decision-making, particularly around vulnerable groups and other marginalized communities.

Listening to speech radio data, especially in local African languages, can be time-consuming and costly. It has been observed that the “offline” community voices are often left out, and without reliable information, these communities may be susceptible to misinformation and make uninformed decisions [49]. Therefore, there is a need to provide a way to mine data from these radio stations in the local languages during a healthcare crisis. This motivates us to explore how to build a radio monitoring pipeline that can be used to mine and obtain community perspectives and insights relevant to guiding government decision-making.

This article builds a radio monitoring pipeline based on previous work on speech recognition models [28, 29, 33] to understand public perceptions and sentiments about the recent Ebola outbreak in Uganda [23]. The monitoring pipeline uses **Automatic Speech Recognition models** (**ASR**) and “human-in-the-loop” analysis to understand public perceptions of government interventions in the Ebola outbreak in Uganda. ASR models improve radio analysis by filtering out Ebola-related conversations from radio broadcasts. The main contributions of this article are as follows:

(1) *We present an end-to-end pipeline for mining and analysing radio speech data.*
(2) *We provide a radio speech dataset for building English and Luganda speech-to-text models.*
(3) *We build and evaluate English and Luganda speech-to-text models.*
(4) *We generate meaningful insights that could guide policymakers in current and future health outbreaks.*

Our results show that different speaker categories were involved in disseminating Ebola-related information on radio broadcasts. The community was knowledgeable about the Ebola signs and symptoms, how Ebola spread in the community and its preventive measures. This was important as it reflected that sufficient information about the Ebola pandemic was being passed down to the community effectively. Finally, our results also show significant differences between the community discussions between male and female community listeners across different topic categories and times of the day.

We analyze how the dissemination of Ebola-related information varied across the speaker categories on the radio. We also provide insights into the community discussions regarding the Ebola outbreak, the community viewpoints, and attitudes toward the government's preventive measures in response to the Ebola outbreak. Finally, we analyse how the discussions about Ebola in the community differ between men and women community listeners. This research shows that understanding the perspectives of "offline" communities is valuable, as governments and policymakers need to obtain such useful information quickly to guide their decision-making.

2 Related Work

2.1 Media Impact on Epidemic Fear

In 2015, the Ebola outbreak in the United States sparked widespread fear among the population, which was significantly fueled by mass media coverage [51]. Researchers employed a mathematical model to examine temporal patterns in Ebola-related online activity, including Internet searches and X (formerly known as Twitter) posts. The study revealed that media coverage accounted for at least 65% of the variance in public behavior related to the disease, demonstrating the profound impact of media on public perception [51]. A single news report could trigger tens of thousands of Ebola-related searches. Similarly, during the COVID-19 pandemic, social media platforms significantly shaped public opinion and behavior, with online campaigns and information exchange contributing to vaccine hesitancy and anti-vaccination sentiments. X, in particular, was a focal point for social media analysis aimed at understanding people's perceptions and behaviors [14, 22].

Hüseyin et al.'s [22] study delved into the reasons for vaccine hesitancy by examining the X behavior of anti-vaccination advocates. Their analysis revealed that nearly a quarter (22.6%) of vaccine-related tweets referenced a specific COVID-19 vaccine, while another 22% expressed anti-vaccination sentiments. The study exposed how social media misinformation significantly influenced the vaccine discourse, perpetuating mistrust in science, conspiracy theories, and skepticism toward vaccine manufacturers and health authorities. These factors contributed to a complex web of influences shaping public attitudes toward vaccines [22]. Furthermore, the COVID-19 pandemic disproportionately affected vulnerable populations in Africa, where online media content analysis revealed widespread economic disruptions, human rights violations, inaccessible healthcare, and educational challenges. This highlighted the need to address these underlying issues to promote vaccine acceptance and public health effectively [7, 46].

A comprehensive media content analysis was conducted across six West African countries, shedding light on the disproportionate impacts of the pandemic on vulnerable populations [46]. Notably, countries with prior experience handling epidemics like Ebola devoted more attention to these impacts, underscoring the significance of past epidemic exposure in informing public awareness and response. While online content analysis has emerged as a crucial tool in infectious disease epidemiology, concerns persist about excluding vulnerable groups due to the digital divide, highlighting the need for inclusive approaches to ensure equitable representation. This research fills this gap by providing a means to understand community perspectives from these "offline" but vulnerable communities.

2.2 Radio for Inclusive Information

Radio is vital in disseminating crucial information, particularly for health-related issues, in African countries with low literacy levels and rural communities [11, 18]. It significantly improves healthcare outcomes by increasing awareness and knowledge among the general population, especially women, on reproductive health and contraception [18]. Radio's unique ability to reach a vast audience, regardless of literacy level, makes it an indispensable tool for promoting health communication in Africa [57].

Previous work by the UN Pulse Lab developed a radio browsing system in African countries like Uganda, leveraging radio's inclusivity to gather vital information for development and relief programs [32]. They developed a system that efficiently monitors radio broadcasts using advanced speech recognition technologies tailored to local Ugandan languages [44], ensuring remote and linguistically diverse communities are heard. Pilot studies focused on refugee influx, local disasters, service delivery, campaigns, and malaria outbreaks [44]. This initiative demonstrates the UN's commitment to inclusivity, utilizing radio's widespread accessibility in Sub-Saharan Africa to capture a broad spectrum of voices and insights, enabling informed decisions that address the needs of vulnerable populations [32].

Radio has emerged as a crucial tool for community empowerment amidst the rapid evolution of mass media [55]. Due to constraints like educational levels, economic conditions, infrastructure, and technological access, radio uniquely bypasses these barriers, providing a reliable and accessible platform for disseminating vital information and indigenous knowledge. Radio's importance lies in its ability to support a bottom-up approach to societal development, making it a vital channel for empowering communities with relevant, localized content [55]. Radio's role underscores its unmatched potential in fostering societal growth and knowledge sharing in regions where modern communication technologies remain out of reach.

2.3 Automatic Speech Recognition and Keyword Spotter Models for Low Resource Languages

Research studies have explored the development of **automatic speech recognition** (**ASR**) and **keyword spotting models** (**KWS**). This work carried out has focused on semi-supervised training of multilingual acoustic models and supervised training of automatic speech recognition and keyword spotting models [25, 28–31, 33, 47]. Menon et al. [32] used advanced neural networks to improve KWS in low-resource languages. They trained a correspondence autoencoder model on bottleneck features, which significantly surpassed the baseline, improving area under the curve, equal error rate, and precision metrics by 8%–12% and 1.7 times, respectively. This approach leverages labeled data from languages with abundant resources and offers new possibilities for supporting underrepresented languages.

Recent studies have addressed the challenge of limited labeled data in building ASR systems, particularly for low-resource languages [8, 24]. For instance, Wiesner et al. [56] developed a

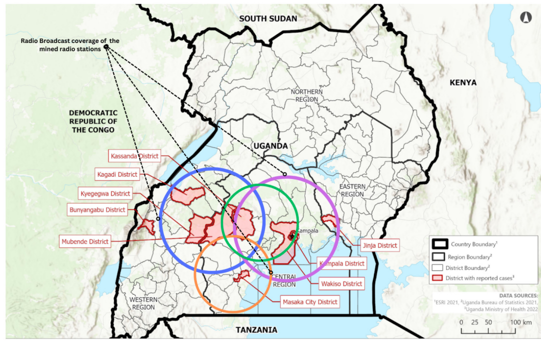

Fig. 1. Ebola virus disease outbreak in Uganda [12].

Kaldi-based ASR system that leverages universal phone modeling and rapid adaptation with minimal transcribed speech. Similarly, Li et al. [24] and Aldarmaki et al. [8] explored few-shot learning and unsupervised methods to overcome ASR data limitations. These approaches have shown promise in resource-scarce environments. Moreover, significant advancements have been made in KWS for low-resource languages [41, 58]. Ng et al. [37] proposed a **contrastive speech mixup** (**CosMix**) learning algorithm for low-resource KWS, consistently improving model performance. Westhuizen et al. [53] focused on feature learning for efficient ASR-free KWS in low-resource languages, achieving a 5% relative performance improvement over baseline **Mel-frequency cepstral coefficients** (**MFCCs**).

Building on these advancements in ASR and KWS, this article leverages existing improvements for radio mining in low-resourced African languages [28, 29, 33]. Furthermore, this study expands on previous work on speech recognition systems for radio monitoring to understand public perceptions and sentiments about the recent Ebola outbreak in Uganda [23].

3 Methodology

This section discusses the end-to-end pipeline for mining and analysing radio speech data. We also provide the radio speech dataset for building English and Luganda speech-to-text models. Finally, we discuss and evaluate the English and Luganda speech-to-text models for the radio data.

On 20 September, 2022, the **Ministry of Health** (**MOH**) in Uganda declared an Ebola outbreak, initially affecting the districts of Mubende and Kassanda [1]. However, the virus rapidly spread to additional districts, including Bunangabu, Kyegegwa, Kagadi, Masaka, Kampala, Wakiso, and Jinja, as shown in Figure 1.

The MOH launched nationwide sensitization and mass communication campaigns to educate the public about Ebola's symptoms and dangers, mirroring previous outbreak responses in Uganda [6, 9]. This critical information was disseminated through various media channels, including local newspapers, television stations, and regular radio talk shows focusing on high-risk communities. Notably, primary radio stations in these districts broadcast in English and Luganda. In this section, we outline the approach to developing a radio monitoring pipeline for the Ebola outbreak in Uganda as shown in Figure 2, comprising three key steps: (a) data collection, (b) speech-to-text model development, and (c) use-case evaluation and analysis. The following sections provide a detailed exploration of each step.

3.1 Data Collection

We collected radio data by streaming radio stations from 06:00 to 23:00 for three months (October to December 2022) across six Ugandan radio stations that covered Ebola-affected areas as shown

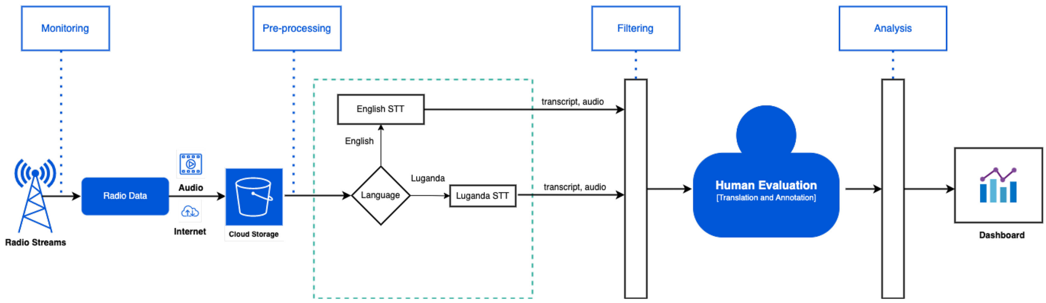

Fig. 2. Approach taken in the radio mining pipeline. The first step is the preprocessing of the audio radio data. This step is followed by the mined radio content's filtering and analysis stage.

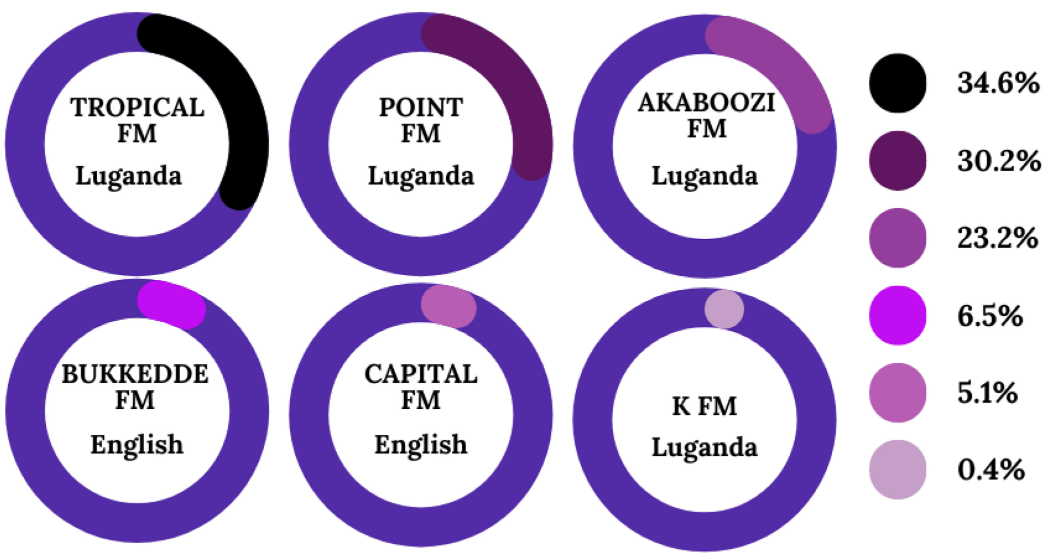

Fig. 3. Six radio stations broadcasting English and Luganda were analyzed for Ebola-related content. The percentages shown represent the proportion of Ebola-related data found in each station's broadcasts compared to the total radio data collected from October to December 2022.

in Figure 1. The selected radio stations broadcast in either English or Luganda. Figure 3 shows the percentage of Ebola radio data analyzed from each station. We prioritized recording times based on live broadcasting schedules of public radios. The data monitoring, preprocessing, filtering, and analysis processes are illustrated in Figure 2. After streaming and preprocessing, we selected a sample English and Luganda radio dataset to train and evaluate the models before deploying them into the data pipeline.

Raw radio data contains various challenges, including background noise, overlapping speech, filler pauses, breaths, incomplete words, silences, laughter, music, mispronunciations, and background music, making it largely unintelligible [33]. To address this, we developed a comprehensive transcription guideline (available on Zenodo[1]) that outlines precise rules for linguists to follow during the radio transcription process. These rules define how to handle different speech nuances. A

[1]https://doi.org/10.5281/zenodo.5855017

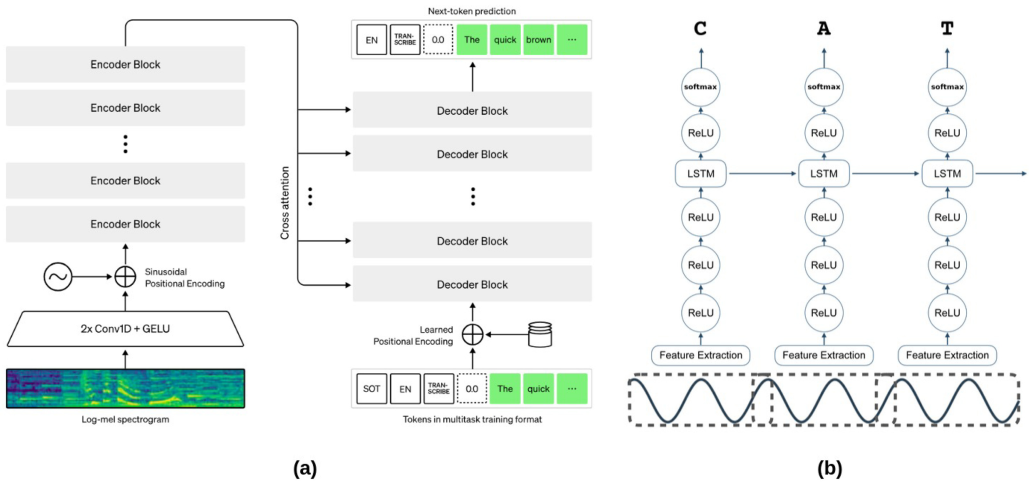

Fig. 4. Architectures for the models used to train both English and Luganda ASR: (a) Whisper ASR Model Architecture and (b) Coqui ASR Model Architecture.

Table 1. Word Error Rates and Accuracy Results on English and Luganda Datasets

Language	WER (%)	Accuracy (%)
English	4.2	95.8
Luganda (Common Voice)	30	70
Luganda (Radio)	47	53

linguist validated every transcribed audio file to ensure compliance with the guidelines, ensuring high-quality transcriptions.

3.2 English and Luganda Speech-to-Text Models

After data collection and transcription, the next step was to train the English and Luganda speech-to-text models. The English ASR model is based on the Whisper model architecture for the English ASR model. Whisper is a pre-trained speech-to-text and speech translation model that can be generalized to many datasets and domains without fine-tuning [45]. The Luganda speech-to-text model is based on Coqui ASR's architecture[2] which is also based on Baidu's Deep Speech research [16] with further improvements. Figure 4(a) shows the Whisper model architecture, while Figure 4(b) shows the Coqui ASR model architecture.

We trained the English ASR model on *1.8 hours* of English radio data and evaluated it on a 20-minute test set to obtain a **Word Error Rate** (**WER**) of 4.2%. We trained a Luganda ASR model on *82.7 hours* of radio data and *162.4 hours* of Common Voice data. The model was evaluated on *1.8 hours* of radio data and *20.3 hours* of Common Voice data. Table 1 shows the English and Luganda ASR model results. Our ASR model achieves significantly better results (95.8%, 70%, and 53%) compared to previous research investigating health-related signals with WER of 61.2% for the English model and 47.53% for the Luganda model [47].

To enhance the accuracy of the Luganda ASR model, we employed cross-lingual transfer learning. We started with a pre-trained English Coqui-STT model and adapted its neural network

[2] https://stt.readthedocs.io/en/latest/Architecture.html

Table 2. Word and Character Error Rates on the Test Set for the Luganda Models

Model	Word Error Rate	Character Error Rate
Coqui ASR	23	9
XLSR-Wav2Vec2	**12**	**3**

Table 3. ASR Model Performance on a Sample of the Luganda Ebola Keyword Words

Keyword	Occurrences	True Positives	False Negatives
ebola	8	8	0
okusaasaana	2	2	0
obubonero	4	4	0
abalwadde	6	6	0
obulwadde	10	5	0
enkungaana	4	4	0
mubende	26	26	0
kassanda	2	2	0
ebyobulamu	5	5	0
eddwaliro	6	6	0
abasawo	16	16	0

parameters for Luganda. This fine-tuning leveraged the existing knowledge from English to improve performance on Luganda data. The training process involved 100 epochs with specific hyperparameters: a 0.2 dropout rate, a batch size of 48, and a learning rate of 0.001. Furthermore, we built a language model to aid the acoustic model in predicting the most likely word sequence. We used the Kenlm toolkit [17] to create a 5-gram language model trained on a text corpus of 240,000 Luganda sentences [34]. Finally, we evaluated the model's performance on a separate Common Voice test set containing *20.3* hours of speech data. The model achieved a WER of *23%*.

We also explored Meta's XLS-R Wav2vec2, a powerful pre-trained model for understanding speech across many languages. We leveraged the Hugging Face library to access a 300-million parameter version of this model[3] and fine-tuned it on Luganda data. The training process involved 50 epochs with a learning rate of 0.0003 per device batch size of 16 and 8 gradient accumulation steps. Similar to the previous approach, we incorporated the 5-gram language model to boost the model predictions. To assess the model, we trained the model on over *113 hours* of speech data, evaluated it on a separate set of *21.5 hours*, and finally tested it on a hold-out set of *21.6 hours*. The model achieved a word error rate of 12% and a character error rate of 3% [34]. Table 2 provides the results of the Luganda ASR Word and Character Error Rates results.

We evaluated different Ebola-related keywords by evaluating the Luganda ASR model's performance for Ebola-related radio content by evaluating different Ebola-related keywords. The keyword list is shown in Table 3 together with the count of the number of occurrences of the keywords. We transcribed *7.5 hours* of radio data using the Luganda ASR model and achieved an F-score of 1.0 on the keyword list. This indicated the model's ability to identify and transcribe Ebola-specific keywords within Luganda speech.

[3] https://huggingface.co/facebook/wav2vec2-xls-r-300m

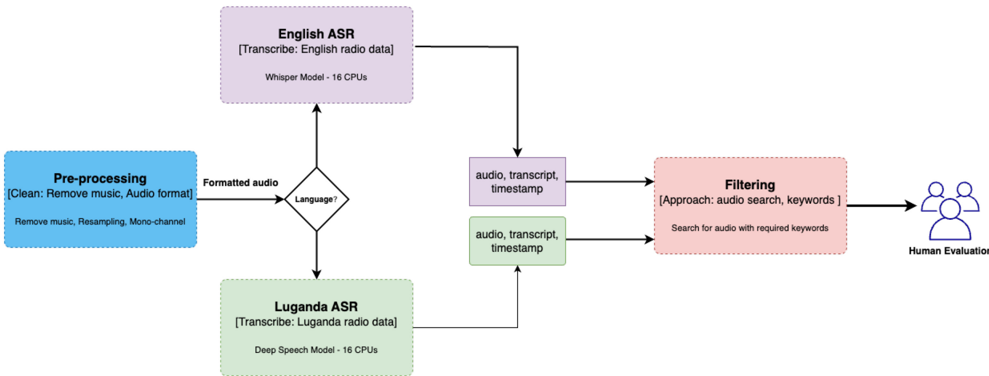

Fig. 5. Deployment of English and Luganda STT models in the radio mining pipeline.

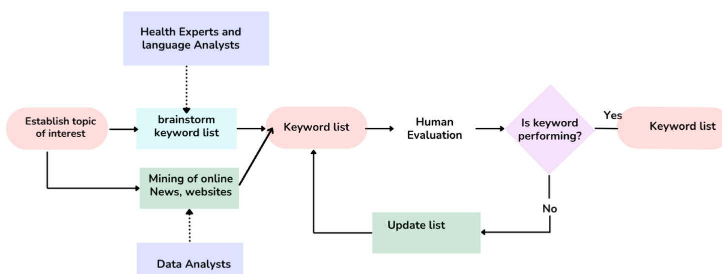

Fig. 6. Keyword selection process.

3.3 Model Deployment

The radio data was preprocessed and directed to the corresponding ASR model based on the language of the broadcast. Leveraging GNU parallel processing, we utilized the English and Luganda ASR models on a Google Cloud Instance with eight virtual CPUs to transcribe the data. The resulting transcriptions were saved as audio, transcript, and timestamp pairs. Subsequently, the data was filtered for keywords related to Ebola and uploaded to a human evaluation tool for further analysis, as shown in Figure 5.

3.4 Use-case Analysis

The analysis involved three steps: (1) Keyword Selection, (2) Human Evaluation, and (3) Data Analysis.

3.4.1 Keyword Selection. Identifying the most relevant keywords for a specific radio-mining topic is a deliberate process. This is because the exact words spoken on the radio can only be determined by listening to the content to provide valuable insights. An example of this was during the COVID-19 pandemic, where words like “president” and “curfew” were significantly more common in health-related discussions than political ones within a specific time frame. To address this, we employed an iterative and incremental approach to keyword selection, refining our list to encompass existing and emerging keywords. As illustrated in Figure 6, this method enabled us to develop a comprehensive list of keywords for mining Ebola-related radio discussions, building on the keywords introduced in Table 3.

Table 4. English and Luganda Keywords used to Filter Ebola-related Discussions from Radio Broadcast Data

Ebola Keywords	
English	Ebola, disease, "ministry of health", Health, cases, outbreak, health worker, recoveries, virus, lockdown, Quarantine, curfew, infection, spreading, equipment, patients, doctors, hospital, testing, gatherings, treatment, vaccine, vaccination, symptoms, bleeding, fever, "yellow eyes", chest pain, vomiting, Diarrhea, victims
Luganda	Mubende, Kassanda, Kyegegwa, Kagadi, Bunyangabu, obulwadde, Minisitule y'ebyobulamu, ebyobulamu, abalwadde, okubalukawo, omusawo, abawonye, akawuka, omuggalo, kkalantiini, kafyu, obulwadde, okusaasaana, ebikozesebwa, abalwadde, abasawo, eddwaliro, okukebera, enkungaana, obujjanjabi, okugema, "ekirwadde ekirimu kitundu", obubonero, "okuvaamu omusaayi", omusujja, "amaaso agakyenvu", "okulumizibwa mu kifuba", okusesema, ekiddukano, abalwadde, "ekirwadde ekibunye ensi"

The data analysts and Luganda language experts formulated the keywords based on their frequency and relevance in Ebola-related content, which they obtained from relevant online news articles and websites discussing Ebola. Once the keyword list was established, the data analysts collaborated with the health experts to verify the Ebola-related keywords. The combined list of keywords formed the initial version of the keyword list. This list was then refined through an iterative human evaluation process, where analysts assessed the effectiveness of each keyword in yielding relevant search results based on the radio data. Keywords that yielded positive results were retained, while those that yielded negative results were removed.

Additionally, analysts identified new Ebola-related keywords mentioned in radio discussions and added them to the list, enhancing its comprehensiveness. The final list of keywords, comprising both English and Luganda terms as shown in Table 4, was used to search radio transcripts and filter out audio files related to Ebola. The search process involved using multiple keywords on a web platform, with the filtered audio files subsequently undergoing human evaluation by analysts.

3.4.2 Human Evaluation. Under the human evaluation stage, we had several predefined "use-case questions" crafted to guide the evaluation and data analysis. To facilitate this process, we broke down the use-case questions into more specific, manageable components. This approach enabled us to extract relevant information from the audio clips and better understand the topics under discussion. We describe how a *use-case question* was simplified into specific questions. An example of the use-case question is: "Who is disseminating information about Ebola, and what information is being disseminated?" An example of the specific questions from the *use case question* are:

(1) Can we identify the speakers talking about Ebola?
(2) Is it a Community, Government official, DJ mention, Advert, Scientist, Guest, Media Personality, or a marginalized group, and so on?
(3) What exactly are the speakers saying?
(4) What is the frequency of dissemination of information about Ebola?
(5) What is the trend in how the different speaker groups disseminate information about Ebola?
(6) What is the trend in how women and men disseminate information?

Table 5. An Example of Human Analysis on a Given Audio to Capture the Details in the Radio Discussion

Questions	**Human Evaluation Annotation and Analysis**
(1) Can we identify the speakers talking about Ebola? (2) Is it a Community, Government official, DJ mention, Advert, Scientist, Guest, Media Personality, or a marginalized group, and so on? (3) What exactly are the speakers saying?	Gender -- *Female* Speaker -- *Community* Symptoms and preventive measures -- *None* Reaction -- *Positive* Context -- *Health* Transcript -- *A health worker who is scared and worried about Ebola will contract the disease and spread it. Interns who are in Mubende will contract and spread the disease because we are informed that senior health workers are not in Mubende because they ran away from the area due to fear of the disease.* *03 October 2022 / Mubende District*

To answer specific questions (1), (2), and (3), we conducted a human evaluation exercise where analysts listened to radio segments identified through keyword searches on a custom dashboard. Each audio file was evaluated to understand if there was sufficient information to answer the predefined questions. The information obtained from the listening-in process included the speaker's gender, speaker category (e.g., healthcare worker, community member), and the information they conveyed about Ebola symptoms, prevention, and overall sentiment. Additionally, analysts captured the conversation's context and created English transcripts for each segment. Table 5 provides an example of how the human evaluation addressed the specific questions.

Through human evaluation, analysts reviewed hundreds of audio clips identified through keyword searches. They listened to each segment and answered predefined questions about the speaker and Ebola discussions for the specific "use-case questions". This evaluation process resulted in a dataset with hundreds of entries.

3.4.3 Data Analysis. We analyzed the human-evaluated data to uncover people's perspectives on Ebola and identify trends in radio discussions. The dataset included details on the date, radio station, speaker demographics, and, most importantly, speaker transcripts. Our analysis involved three key steps: data preparation and cleaning, **exploratory data analysis** (**EDA**), and finally, modeling.

— **Data Preparation and Cleaning:**We cleaned the downloaded data, removed irrelevant entries, and ensured accuracy. This included techniques like removing stop words, converting text to lowercase, and handling abbreviations. Additionally, we lemmatized words and expanded contractions for consistency.

— **Exploratory Data Analysis:** To gain insights from the radio transcripts, we employed several techniques that included:
  – Word cloud visualizations that highlight frequently used words and a quick overview of prominent themes in the data.
  – N-gram Analysis where the sequences of words (n-grams) were captured to identify recurring patterns and phrases, preserving context.
  – Sentiment Analysis that categorized the transcripts as positive, negative, or neutral, revealing the overall sentiment of discussions and potential perception trends.

— **Data Modeling:** We explored various methods to extract valuable information from the transcripts:
  – Topic Modeling: Using algorithms like **Latent Dirichlet Allocation** (**LDA**) and **Non-Negative Matrix factorization** (**NMF**), we uncovered underlying themes in the data, allowing for better organization and summarization.
  – **Term Frequency-Inverse Document Frequency** (**TF-IDF**): This technique identified keywords with high importance within specific transcripts compared to the entire dataset, highlighting relevant sentences.
  – spaCy: This library provided functionalities like tokenization (breaking text into units), part-of-speech tagging (identifying word types like nouns or verbs), and named entity recognition (extracting named locations or people), enabling deeper text exploration.
  – BERT (Bidirectional Encoder Representations from Transformers): This pre-trained model considered the surrounding context of keywords to enhance understanding of the transcript's meaning.

4 Results

In this section, we discuss the results of our study by answering the three research questions corresponding to the "use-case questions" that the analysts had to answer.

4.1 RQ1: How did the Dissemination of Ebola-related Information Vary Across Different Speaker Categories?

This research question explores how Ebola-related information was disseminated through radio conversations during the Ebola epidemic. Specifically, we investigate:

— *RQ1.1: Who were the speakers participating in the radio conversations?*
— *RQ1.2: What Ebola-related information did the speakers disseminate?*
— *RQ1.3: What were the daily communication trends across the speaker categories?*

By examining these aspects, we aim at gaining a deeper understanding of how radio played a role in sharing information during the Ebola epidemic.

4.1.1 RQ1.1: Who were the Speakers Participating in Radio Conversations? We employed human evaluators to identify and categorize speakers engaged in Ebola-related radio conversations. Our analysis yielded a comprehensive classification as presented in Table 6, which reveals three primary categories of speakers: *community*, *government*, and *media.*

— The *community* category comprises individuals who actively participated in radio discussions, including callers to talk shows and community members interviewed on-air.
— The *government* category includes high-ranking officials such as the president, ministers, members of parliament, district health personnel, health officers, and association leaders, who shared their perspectives and expertise on the Ebola crisis.

Table 6. Speaker Categories Identified from the Radio Conversations

Category	Subcategory	Description
Community	Community listeners	Radio callers
	Guests	Community speakers hosted on radio talk shows
Government	Government officials	Government speakers such as the President and ministers
	Scientists	Speakers from the medical/health domain
	Adverts	Radio adverts from government bodies like the Ministry of Health.
Media	Media Personality	Radio news readers and journalists
	DJ Mentions	Music radio show presenters and hosts

— The *media* category encompasses radio talk show hosts, news anchors, and journalists who play a crucial role in disseminating information.

From the data analysis, government advertisements dominated the radio conversations with 255. These were followed by media personalities with 188 conversations; government officials accounted for 188 radio conversations; community listeners had 80 radio conversations; and radio guests and scientists had less than 20 radio conversations. This indicates the significant impact of government advertisements on the radio conversation landscape during the Ebola crisis.

When the Ugandan government announced an Ebola outbreak, this sparked radio discussions from the community. Between September and October, government officials, media personalities, and scientists actively participated in conversations about Ebola's signs, symptoms, and prevention measures. Our analysis of radio broadcasts revealed varying discussion intensity across different groups. For instance, by November 2022, while media personalities' on-air discussions about Ebola decreased, Ebola-related adverts surged, as depicted in Figure 7. Community engagement notably increased in November and rose in December, coinciding with the end of the Ebola lockdown. This significantly heightened community interest and discussions about Ebola prevention and control measures.

4.1.2 RQ1.2: What Ebola-related Information did the Speakers Disseminate? To better understand how Ebola-related information was transmitted from October 2022 to December 2022, we examined the content shared by different speaker categories. Our goal was to track how the dissemination of information evolved over time. Figure 8 shows the relative percentages of dissemination of Ebola information by different speaker categories across the three months. This allows us to see how other groups (e.g., community, government officials, guests, scientists) contributed to the public conversation about Ebola during this period.

We provide summaries of extracted Ebola conversations across the three speaker categories and highlight any changes in conversations across the speakers from October to December.

— **Community**
  - Community engagement surged from 4.9% in October to 11.4% by December, indicating growing public involvement in discussions around the outbreak's impact and response measures. Initially, concerns focused on the lockdown and Ebola's effects in October. In November, the emphasis shifted to compliance, frustrations over the government restrictions, and healthcare access challenges. By December, discussions centered on recovery, gratitude for lifted restrictions, and hopes for the future, with community members sharing personal stories and plans for rebuilding.

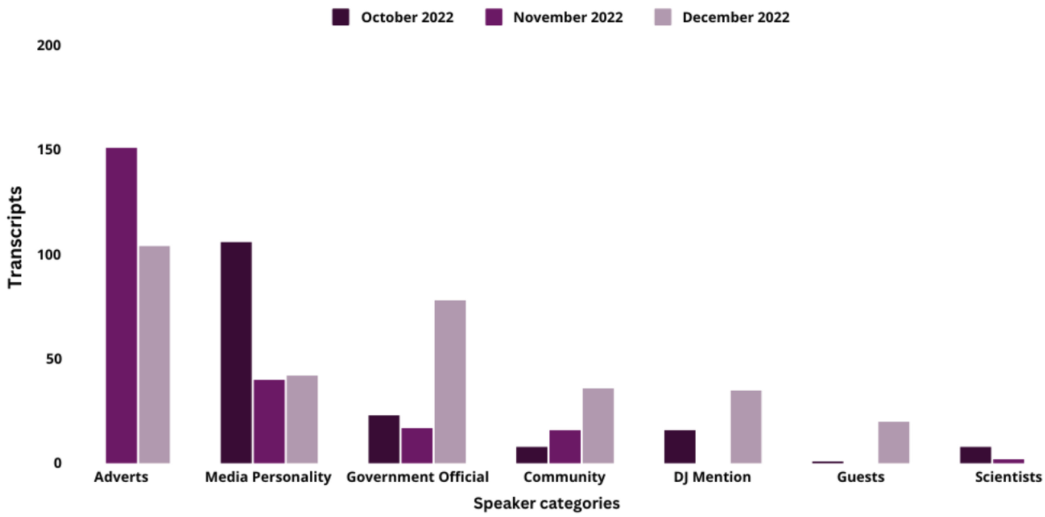

Fig. 7. Frequency of speaker participation in Ebola-related conversations from October to December 2022, detailing monthly involvement of various categories like adverts, media personalities, government officials, and community.

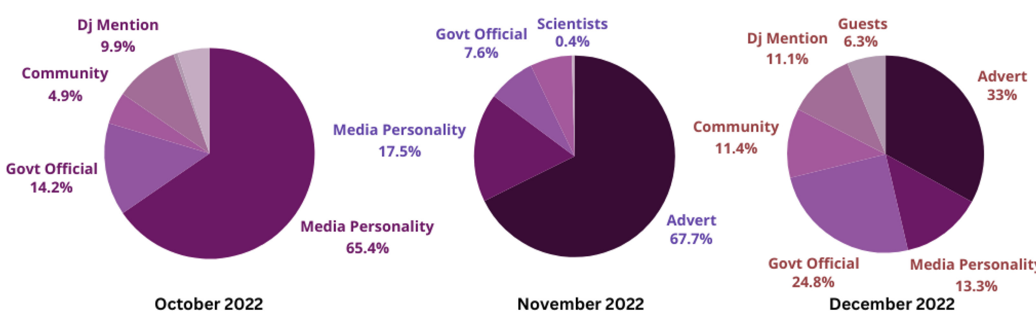

Fig. 8. Monthly breakdown of Ebola-related radio conversations by speaker category, expressed as proportions of the total transcripts examined from October to December 2022, highlighting how the distribution of information changed over the months.

  – Guest discussions increased from minimal in October to 6.3% in December, offering diverse perspectives on the outbreak's management and future prevention. Initially, guests criticized the government's response and its impact on tourism. Later, they discussed community impacts, government preparedness, and the crucial roles of continuous education and community leaders in crisis management. The narrative shifted from criticism to lessons learned and vigilance, emphasizing the importance of sustained awareness even after lockdown measures were lifted.

— **Government**
  – The contributions from government officials decreased from 14.2% in October to 2.8% in December, reflecting a shift from emergency declarations to routine updates as the crisis stabilized. Initially, officials focused on addressing the Ebola situation (October), then shifted to managing Ebola (November), and finally expressed relief and hope for recovery (December).

    - For the advert category, we observe a surge from 0% in October to 67.7% in November, coinciding with the outbreak's peak and stricter safety measures. As the outbreak waned, adverts halved to 33% in December, focusing on sustained prevention and community vigilance. The adverts aired in November emphasized public awareness and adherence to health guidelines, while December adverts encouraged cooperation and trust in health officials to contain the disease.
- **Media**
    - Media personalities played a crucial role early on, dominating with 65.4% in October. They alerted the public and shared urgent information about the outbreak. As the outbreak progressed, their role shifted to less frequent but crucial updates, covering topics like the aftermath of the lockdown, economic challenges, and community gratitude.
    - DJ mentions provided consistent outreach, increasing slightly from 9.9% in October to 11.1% in December. DJs relayed urgent public health messages and updates throughout the outbreak, using engaging content to capture the audience's attention. They urged people to take Ebola seriously, discussed the impact on daily life, and emphasized the importance of following health guidelines.

We identified critical differences in conversations across speaker categories. The analysis revealed that government officials primarily focused on implementing Ebola prevention guidelines and **standard operating procedures** (**SOPs**). In contrast, media personalities mainly discussed Ebola, sharing updates on new cases and related programs. The community members emphasized the importance of following government guidelines and the need for support services for Ebola survivors, including mental health support and food relief programs. These community discussions played a vital role in amplifying the voices of those affected by the Ebola outbreak, providing a platform for their concerns and needs to be heard.

4.1.3 RQ1.3: What were the Daily Communication Trends Across the Speaker Categories? To understand which speaker categories contributed Ebola-related information on different days, we visualized their daily contributions as shown in Figure 9. The analysis reveals that:

- Advertisements were consistently aired throughout the week, mostly on Fridays.
- Community contributions peaked on Fridays, coinciding with music show programs when DJs frequently mentioned Ebola.
- Government officials were most active from Tuesday to Saturday, with a pause on Sunday for rest and religious services.
- Guests discussed Ebola primarily on Fridays and Sundays, avoiding weekdays when productivity is high.
- Media personalities disseminated information about Ebola mainly from Monday to Friday, aligning with their radio programs while reserving weekends for entertainment.

This analysis provides valuable insights into the daily patterns of Ebola-related discussions across various speaker categories.

4.2 RQ2: How did the Community in Uganda React to the Ebola Outbreak, and how did their Views on the Government's Response Measures Influence their Actions?

This research question explores how Ebola-related information was disseminated through radio conversations during the Ebola epidemic. Specifically, our analysis delved into community perceptions of the Ebola virus signs and symptoms, treatment and vaccination options, and the spread of Ebola and its prevention. We sought to understand the community's knowledge, beliefs, and concerns regarding these critical aspects of the Ebola outbreak, informing effective public health responses and community engagement strategies.

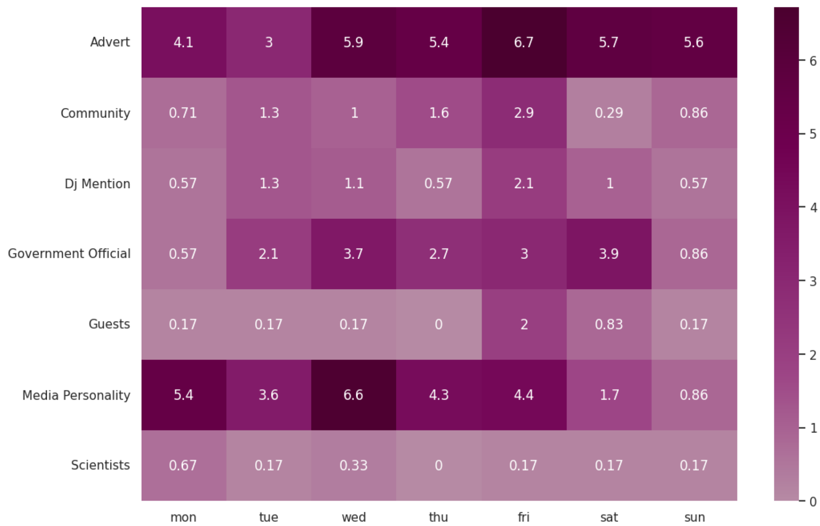

Fig. 9. Weekly distribution of speaker participation in Ebola-related radio conversations over three months of the ebola period, categorized by day and speaker type. It represents percentages relative to the entire dataset of analysed transcripts, showing varying engagement levels correlating with typical weekly activities and broadcast schedules in Uganda.

Specifically, we investigate:

- *RQ2.1: What were the community discussions on Ebola virus signs and symptoms?*
- *RQ2.2: What were the community discussions and perceptions on the Ebola vaccines?*
- *RQ2.3: What were the community discussions on Ebola transmission?*
- *RQ2.4: What were the community perceptions toward the government's preventive measures in response to the Ebola outbreak?*

4.2.1 RQ2.1: What were the Community Discussions on Ebola Virus Signs and Symptoms? Figure 10 summarizes the key findings of the community discussions on Ebola signs and symptoms.

Community radio discussions on Ebola symptoms revealed that Diarrhea, vomiting, and fever were the most frequently mentioned symptoms, while fatigue, muscle pain, and sore throat were less discussed. Interestingly, discussions on symptoms like fatigue and muscle pain were more prevalent among females. While males dominated discussions overall (80%), this doesn't necessarily mean they were more affected than females. Females were more open to discussing symptoms like fatigue and muscle pain, which are often initial signs of Ebola. Notably, the data suggests discussions peaked when the Ebola disease was more advanced, with vomiting and diarrhea being mentioned more than initial symptoms like fever and fatigue, highlighting the importance of timely public health responses. Figure 11 illustrates the frequency of discussions on various Ebola-related signs and symptoms, providing insight into the community's awareness and concerns. The results also highlight more males, with 79.8%, than females, with 20.2% engagements in the radio conversations.

The community emphasized the importance of recognizing Ebola's signs and symptoms, including fever, vomiting, diarrhea, and abdominal pain, as confirmed by health workers [21]. Table 7 shows a transcript of a community member discussing Ebola symptoms and highlights the community's emphasis on adhering to preventive measures. Community members discouraged self-medication and stressed the importance of seeking professional medical help, aligning with WHO

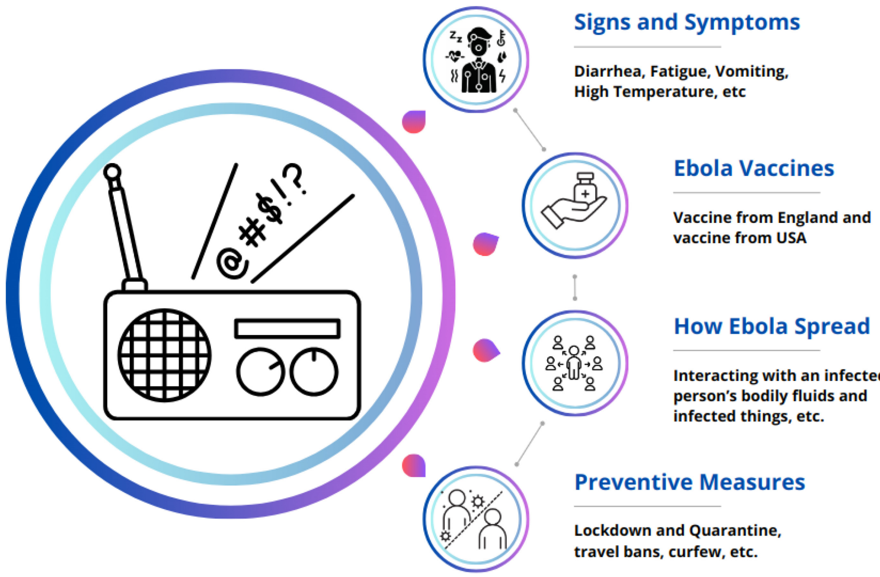

Fig. 10. Key findings from radio conversations during the Ebola outbreak highlighting community discussions on Ebola symptoms, vaccine awareness, and preventive measures.

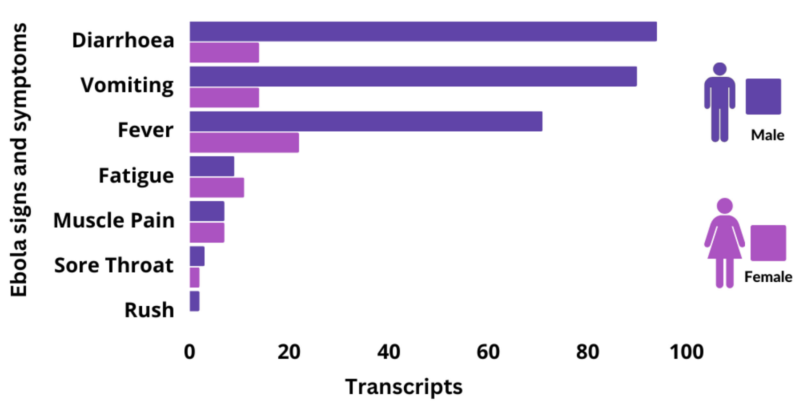

Fig. 11. Frequency and gender distribution of discussions on Ebola signs and symptoms, highlighting the most prevalent symptoms like diarrhea, vomiting, and fever, and a significant male majority in these discussions.

recommendations [3]. The table also provides the keywords used by human annotators to extract relevant conversations and an example script.

4.2.2 RQ2.2: What were the Community Discussions and Perceptions on the Ebola Vaccines? Despite no licensed vaccines being available in Uganda, as reported by WHO [2], the WHO and Ugandan government considered using Ebola vaccines during the outbreak [10, 54]. Community discussions on the radio revealed perceptions and awareness of Ebola vaccines. Most mentions (65.8%) referred to vaccines from England, while 34.2% mentioned vaccines from the USA. However, some community members mistakenly referred to the Oxford and Sabin vaccines for treatment against Polio and COVID-19, respectively. This highlights the need for accurate information dissemination

Table 7. English and Luganda Keywords used to Extract Conversations about Ebola Signs and Symptoms

Sample Keywords	Context of Conversation
English [*Signs, Symptoms, Pain, and Fever*]	The conversation focused on the public health warning and information about the signs and symptoms of Ebola and urged people to be careful and follow preventive measures due to the Ebola outbreak.
Luganda [*obubonero, abasawo, abalwadde*]	A community member said, "People should be cautious about Ebola symptoms. Anyone who comes across a person with Ebola symptoms should report it immediately to health workers. Health workers should also put on protective gear when handling these patients. No one should go to traditional healers to get treated for Ebola. The same applies to religious leaders; people should not go to seek prayers from them under the guise of treating Ebola."

Table 8. Summary Context of the Conversation that could be Extracted using Keywords Related to Ebola Vaccines

Sample Keywords	Context of Conversation
English [*Vaccine, Vaccinate, Treatment*]	The conversations contained information regarding the vaccination efforts against Ebola. They also included community opinions and concerns about the vaccination process and the government's response to Ebola.
Luganda [*okugema, okukebera*]	A member of the community said, "Surely I do not agree with the arrangements they have set up for testing [trying out the] Ebola vaccines on us, they have bodies they should start with their bodies, but that doesn't work for us because some of us we did not vaccinate for COVID"

in pandemics. Government and community speakers dominated the discussions, with the government aiming at providing vaccines to affected communities. The community members expressed concerns about untested vaccines, as shown in Table 8. Table 8 shows a transcript of a community member discussing the Ebola vaccines. The table also provides the keywords used by human annotators to extract relevant conversations and an example script.

4.2.3 RQ2.3: What were the Community Discussions on Ebola Transmission? Analyzing community perceptions of Ebola transmission revealed three key themes: *contact, transmission,* and *spread.* Discussions centered heavily on direct contact with infected individuals or contaminated surfaces. Discussions on the spread and transmission followed these.

The focus on *contact* in these discussions highlights a dominant community concern: infection through direct contact with infected people or contaminated surfaces. In contrast, discussions about *spread* likely reflect anxieties around community interactions or outbreaks with unclear initial contact points. Notably, fear of Ebola's spread was significant, especially among healthcare workers, a genuine concern for those risking their lives to care for patients [53]. Table 9 shows a transcript of a community member discussing the spread of Ebola. The table also provides the keywords used by human annotators to extract relevant conversations and an example script.

4.2.4 RQ2.4: What were the Community Perceptions Toward the Government's Preventive Measures in Response to the Ebola Outbreak? As the Ebola virus spread in the community, the Ugandan government imposed lockdown measures in the affected districts to contain its spread.

Table 9. Summary Context of Conversation that could be Extracted using Keywords Related to the Spread of Ebola in the Community

Sample Keywords	**Context of Conversation**
English [*Spread, Transmission*]	The conversation revolves around concerns and actions related to the spread of Ebola, including the fear of healthcare workers contracting and spreading the disease, efforts to limit the virus's spread through contact tracing and isolation, and legal actions taken against individuals and vehicles violating quarantine and curfew directives due to Ebola.
Luganda [*okusaasaana, omulwadde*]	A member of the community said, "I can not hug you, and I can not shake hands with you because Ebola is out there. Ebola is dangerous, and it can spread from one person to another. To avoid contracting Ebola, wash your hands regularly with water and soap; if you have had physical contact with any Ebola patient, call the health authorities."

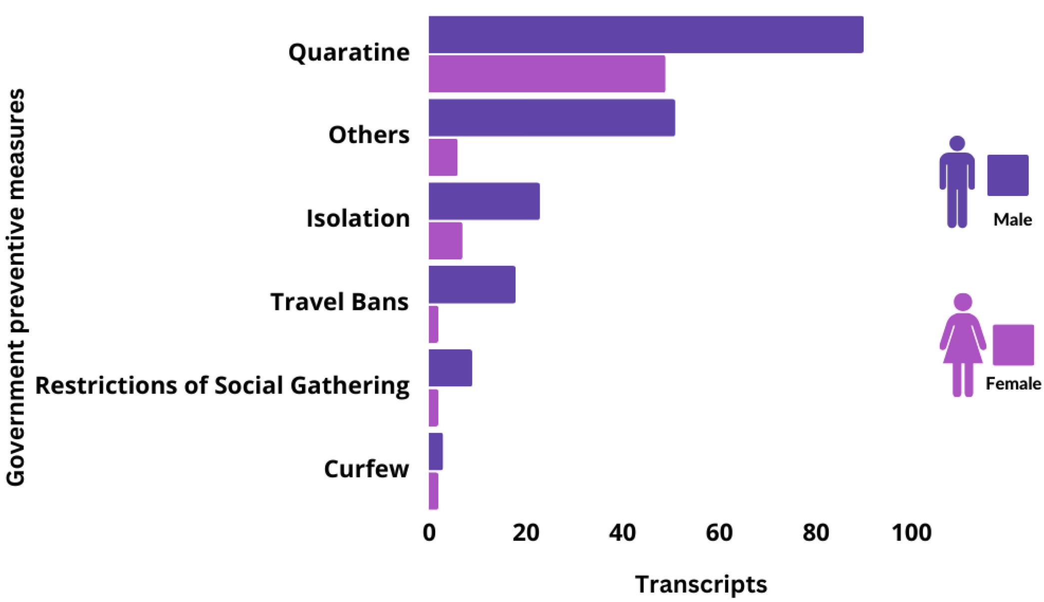

Fig. 12. Distribution of gender participation in discussions on ebola preventive Measures, highlighting the community's focus on quarantine, isolation, and other government-imposed measures, with 74% male and 26% female participation. The "Others" category represents additional preventive measures not explicitly listed but discussed by the community.

The lockdown measures impacted community livelihoods. We analyzed community perceptions of these measures, presented in Figure 12.

The bar chart shows that quarantine was most frequently discussed, followed by curfews, travel bans, and other measures. However, also reveals a concerning gender imbalance, with males dominating discussions (74%) and females dominating 26% of the conversations. Table 10 provides keywords and examples of community discussions on lockdown measures. Our analysis highlights the importance of understanding public perspectives on Ebola preventive measures, including quarantine, curfews, and travel bans and addressing the gender imbalance in these conversations. These

Table 10. Summary Context of Conversation that could be Extracted using Keywords Related to Lockdown Measures

Sample Keywords	Context of Conversation
English [*Prevention, lockdown, Quarantine, Isolation, Curfew, and so on*]	A community member said, "The sixty-three days have not done us good, but I want to thank the president and the prime minister XXX for hearing us out. If they extended the lockdown, we would feel bad, and some of us would leave the Mubende district because we had nothing to eat, and we are happy that we have returned to work."
Luganda [*omugalo, Kasanda, ebola*]	The community member said, "If the Ministry of Disaster Preparedness still exists, this is where the people of Kasanda and Mubende need its intervention because the Ebola lockdown has hit the economy down and people are no longer concerned by Ebola but only their finances."

findings highlight the outbreak's impact and the need to address the effectiveness of implemented measures and the gender gap in community engagement in radio conversations.

Table 10 shows a transcript of a community member discussing the government lockdown measures. The table also provides the keywords used by human annotators to extract relevant conversations and an example script.

We obtained a baseline from the human evaluation process for our subsequent analysis, allowing us to identify and summarize the public's perspective toward Ebola preventive measures.

— *Quarantine and isolation:* The Ugandan government's quarantines and lockdowns to contain Ebola's spread significantly impacted communities' daily lives and economic stability. While necessary for public health, these measures presented substantial challenges. Community opinions varied; some supported isolation and lockdowns and believed it was vital to isolate Ebola patients and trace their contacts, while others expressed concerns about adverse effects. Food support emerged as crucial during quarantines and lockdowns, highlighting the need for a compassionate approach.

— *Travel bans:* Community members were concerned about the impact of travel bans on their daily lives, including accessing food, work, and education. Although necessary to prevent the virus's spread, travel bans disrupted daily routines, affecting commerce, education, and essential services.

— *Restriction of social gatherings:* Community discussions emphasized the importance of preventive measures like social distancing and avoiding crowded places. Limitations on social gatherings led to discussions on collective action in fighting the outbreak. Radio discussions highlighted the need for vigilance, staying informed, and adhering to guidelines, with the sentiment "By staying apart, we stand together against Ebola" which captured the shared commitment to overcoming the virus.

Other preventive measures included isolation and curfews. Isolation sparked intense conversations, blending fear, compassion, and hope. The community members shared recovery stories and encouraging messages, weaving a narrative of hope. Curfews, especially their enforcement, were discussed, which sparked debates on freedom and the community's safety.

4.3 RQ3: How did Gender Dynamics Influence Ebola Community Discussions on Radio?

Understanding the gender dynamics in community discussions about Ebola is crucial for effective prevention and control strategies. Our analysis of radio conversations revealed differences in

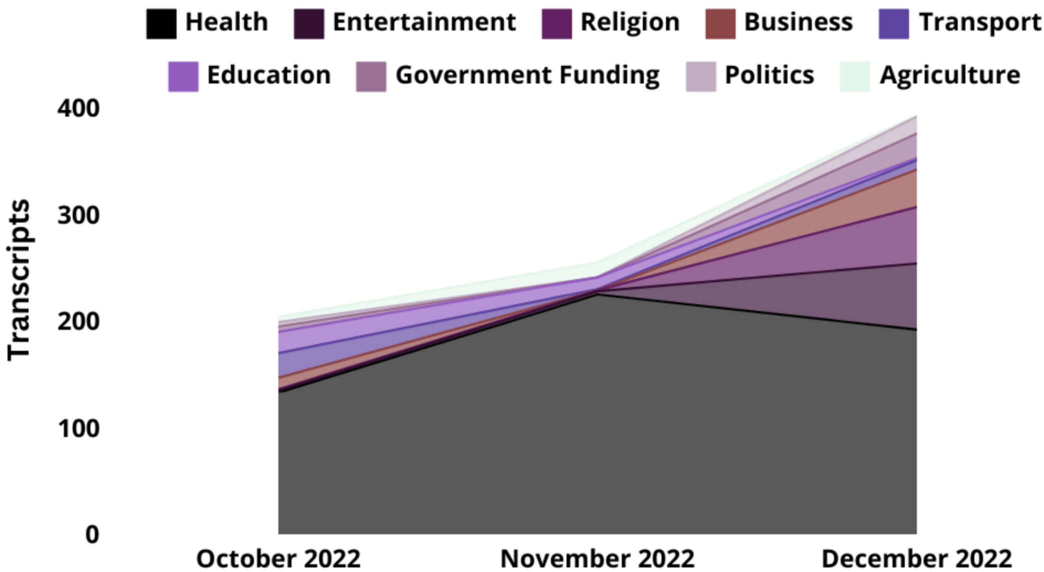

Fig. 13. General frequency of subjects discussed on the radio from October to December, with a comprehensive view of the varying engagement across topics such as health, entertainment, and education, highlighting significant peaks and shifts in public discourse over three months.

topics discussed and sources of information used by men and women during the outbreak. Before examining these differences, it is essential to understand the overall discussion trends.

Figure 13 presents a stacked area chart of radio discussion topics from October to December. The "Health" topic dominated the conversations, with transcript counts of *133* in October, *225* in November, and *192* in December. This was likely due to ongoing public health concerns, including Ebola prevention, symptoms, and vaccines. The peak in November is possibly related to specific events or health issue escalations. Discussions around the "Entertainment" topic were minimal in October and November but significantly increased to *192* in December. This was possibly due to holiday-related activities. The discussions around the "Religion" topic had fewer mentions in October and November but increased to *53* in December. This could be attributed to the religious events or holidays around this month.

The "Business" topic had several discussions in October but did not have any mentions in November but rose slightly to *35* in December. Discussions around the "Transport" sector had *23* mentions in October but reduced in November and December. The "Education" topic had *20* times in October, which was reduced in November and December. "Government Funding" had an initial interest in October but had no mentions in November, and an increase to *23* mentions in December, possibly due to end-of-year budget discussions.

"Agriculture" discussions were initially low with *5* mentions in October, peaked at *14* in November, then dropped in December, indicating possible resolved issues or shifted public interest. This means shifting community priorities and responses to the Ebola outbreak. Figure 14 shows the total number of transcripts identified with contributions from male and female community speakers. The results show that 76% of the Ebola-related conversations were from male speakers compared to 24% of the radio conversations from female speakers.

From the analysis of the transcripts, specific topics were highlighted by male and female community listeners. While both male and female listeners discussed broader topics like education

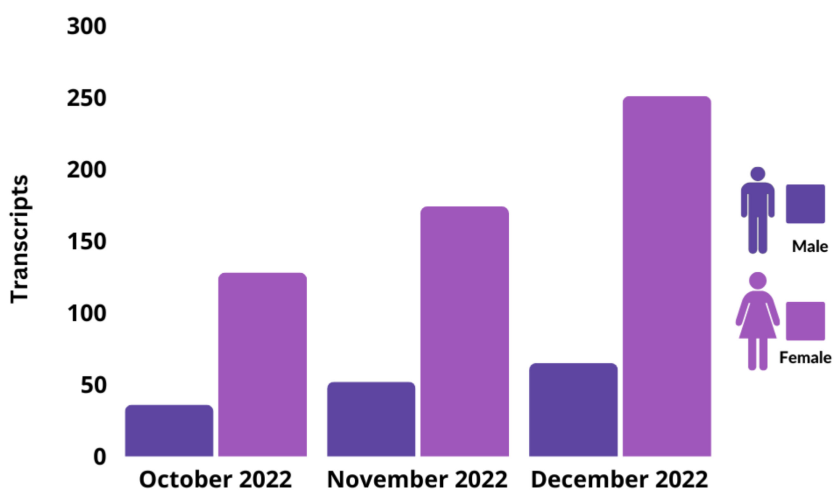

Fig. 14. Gender-based participation in radio conversations from October to December 2022.

and food security, the female listeners additionally expressed more concern about topics such as domestic violence and the strictness of security measures.

4.3.1 Gender Differences in Community Discussions. An analysis of community contributions across various Ebola-related subjects reveals different gender-specific contributions as shown in Figure 15. While males dominated discussions on health topics, contributing significantly more instances than females, this disparity narrowed for business and entertainment subjects. Notably, female community participants led discussions on food scarcity, suggesting a potential difference in priorities or areas of concern. The contributions were minimal for other subjects like transport and government funding but with a more balanced gender distribution.

4.3.2 Fluctuating Engagement Over Time. The line graph in Figure 15 showcases how community engagement on various Ebola-related subjects changed over the three-month period (October-December). The subject of health peaked in November, suggesting a heightened response as the outbreak potentially reached its peak. Similarly, discussions on government funding showed an upward trend toward December. This could indicate growing calls for support after the implementation of lockdown measures. Conversely, contributions related to business and food scarcity declined from October to December, possibly reflecting a shift in community priorities and potentially an improvement in these areas. Notably, discussions on transport and entertainment remained relatively low and consistent throughout the period, suggesting a more constant interest in these topics.

4.3.3 Timing of Radio Conversations. An analysis of radio schedules revealed interesting gender differences in participation during Ebola conversations. Women engaged in radio conversations during news hours as shown in Figures 16 and 17.

This suggests women participated more in news segments than in other programs. In contrast, men consistently participated throughout the day, as shown in Figures 16 and 17. This might be because men hold more radio program leaders and host positions. Additionally, based on Figure 17, we deduced the following proportions for different parts of the day: 39.2% of the data came from morning conversations, 26.8% from evening conversations, 24.1% from afternoon conversations, and 9.9% from nighttime conversations.

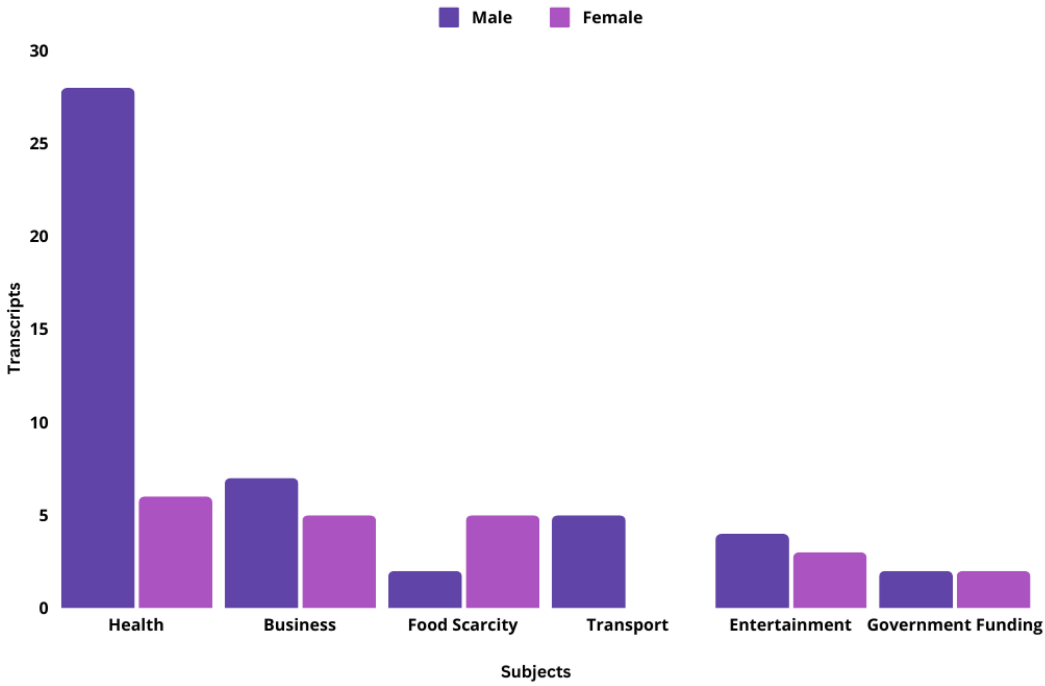

Fig. 15. Gender-specific contributions to discussions on various Ebola-related subjects over three months, highlighting the dominance of male contributions in health-related discussions, while females more frequently discuss food scarcity.

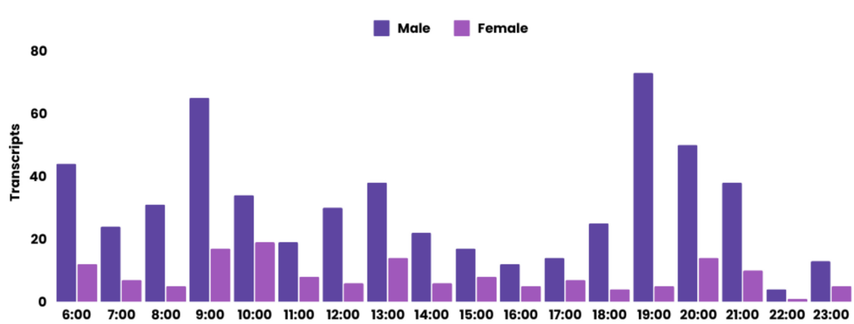

Fig. 16. Timing of male and female participation in Ebola-related radio conversations, illustrating hourly engagement trends that show continuous male involvement and concentrated female participation during specific news hours.

5 Discussion

This study analyzed radio conversations during an Ebola outbreak in Uganda to understand public communication and perceptions. Our findings revealed that three main speaker categories participated in radio conversations: Government, community and media. The government made the most significant effort to educate the public about the Ebola outbreak. This aligns with previous efforts by African governments and Ministries of Health to take vital leadership roles in educating the population about infectious disease outbreaks [39, 43, 48]. Community discussions focused on

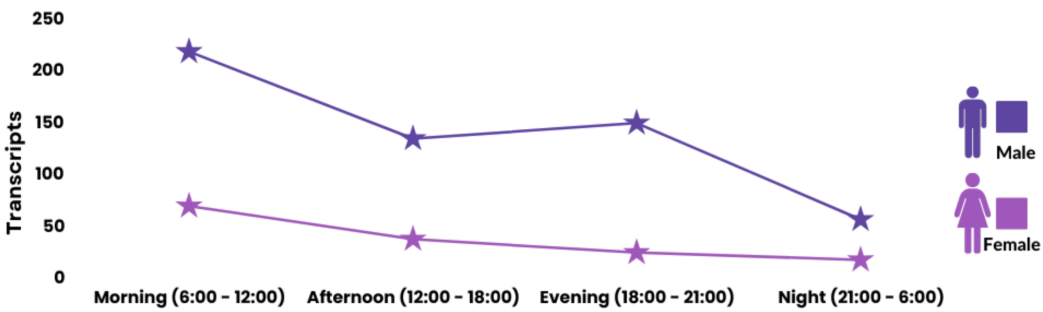

Fig. 17. The line graph illustrates the time distribution of gender participation in Ebola-related radio conversations, a gradual decline in participation from morning to night, highlighting the dynamic engagement patterns across the day.

Ebola virus signs and symptoms, perceptions of the introduction and use of Ebola vaccines, and perceptions of Ebola transmission. Our results show that the community was hesitant about using Ebola vaccines, mirroring past concerns during COVID-19 hesitancy in the communities in Uganda [20, 38].

We analysed the community's perceptions concerning the government's preventive measures, such as the quarantine of affected populations, travel bans in the affected districts, lockdowns, and restrictions on social gatherings. The analysis showed that some community members were unwilling to tolerate more restrictions from the government because of their impact on business, education, and agriculture, which had already been affected by the COVID-19 lockdown measures. The recommendations for government and policymakers are:

— Community engagement is essential during a healthcare crisis, and listening to community voices during a healthcare crisis is crucial.
— Develop targeted communication campaigns addressing vaccine safety and efficacy in health crises, for example, leveraging trusted voices in the community.

We also analyzed differences between male and female community members' discussions and perceptions of the Ebola outbreak. The analysis of the radio broadcast data revealed differences in the content and the times of the conversations for the male and female speakers. Overall, we observed more male than female participation in the radio discussions. The difference in contribution can be attributed to the ownership of mobile phones in rural areas, which is higher in males than females [52]. The findings showed that most women's participation was predominantly from interviews conducted by news journalists, highlighting their significant involvement during news segments compared to other segments of radio talk shows. This shows that women are underrepresented in the radio data and aligns with existing evidence on how men and women engage differently with media and digital technologies, possibly due to mobile phone and radio ownership disparities. As radio is a public space, men feel more confident doing so because of how they are socialized. We also observe that women's access to phones is often shared due to the digital gender divide, and as such, their participation is limited during the day [4, 26, 40].

Government and policymakers could recommend encouraging women's participation in radio discussions by creating safe spaces and addressing potential barriers like childcare and access to phones.

Based on the analysis of the topics discussed, the Ebola-related conversations from both men and women predominantly revolved around health, religion, business, entertainment, education, and government funding. However, women's conversations mentioned domestic violence, which was absent in men's conversations. In the business category, both male and female listeners were concerned about the struggling businesses during the lockdown. This was primarily among the informal working sector in the transport business, for example, the *boda boda* (motorcycle taxi) and public taxis. In the education topic, listeners were concerned with the difficulties the learners and teachers faced during the lockdown period. There were discussions around food security from the female listeners compared to the male listeners, as the females are usually the carers in the home.

The radio discussions on domestic violence and security were only raised by female listeners. They were concerned about the challenges of fighting domestic violence during the Ebola and COVID-19 lockdowns, as evidenced by other countries with the Ebola disease outbreak [42]. They were also concerned about human rights abuses by the police while enforcing Ebola preventive measures. While the government relied on police to enforce lockdown measures, their involvement in the Ebola virus response could further erode public trust in government institutions by the community [19].

As demonstrated by this research, machine learning can significantly enhance analytics for health communications. However, engaging with local communities, health officials, and policymakers in real time is essential to ensure the sustainability and effectiveness of health communication strategies. Future research should focus on developing frameworks for community engagement to ensure communication strategies are based on evidence and community input. It should also explore the integration of machine learning with real-time broadcasting, allowing broadcasters to adjust messages in response to changing circumstances or feedback from the community.

This work provides evidence for a research gap in analysing discussions from "offline" communities. These communities usually do not have access to the Internet and social media platforms, and their concerns and perceptions are often ignored. Radio provides a platform for in-depth conversations from the community that may not be sufficient on social media platforms. It has also been observed that radio listeners are usually more engaged with content than social media users, who quickly scroll through the various posts on the platforms. Finally, radio conversations are usually unscripted and spontaneous; we believe these conversations lead to more authentic views of the community listeners. While our study provides valuable insights from radio data, our future research will integrate data from other media sources, such as social media and direct community feedback, to comprehensively understand public perceptions. This approach could be essential in managing public reactions during the early stages of a health crisis, where timely and effective communication is crucial.

6 Conclusion

Radio remains a vital source of information in sub-Saharan Africa, serving as a platform for public discourse and opinion formation through phone-ins and radio talk shows [44]. This rich data source offers valuable insights for developing solutions that directly address the needs of "offline communities". This article explores state-of-the-art deep-learning speech recognition techniques to understand public perceptions and perspectives during the 2022 Ebola outbreak in Uganda. We build Automatic Speech Recognition models to analyze radio broadcast data in English and Luganda, a local language in Uganda, from six radio stations between October and December 2022.

Our analysis revealed significant variations in Ebola-related information dissemination depending on the radio speaker category. Furthermore, we uncovered valuable insights into community discussions surrounding the Ebola outbreak, including public perceptions and attitudes toward government preventative measures. These findings offer crucial information for policymakers and health officials, illuminating how government and communities discuss health issues. Interestingly, the analysis showed active participation from both men and women in radio discussions about the outbreak. However, the timing and specific concerns raised differed between genders. Importantly, the study highlights radio as a powerful tool for government communication, enabling information dissemination alongside gathering public perspectives on current issues. Using local languages further amplifies the government's reach to these communities. This research demonstrates the potential of machine learning to automatically and efficiently analyze radio broadcasts, providing a window into community views. By understanding public perspectives on government initiatives, such as those driven by the Ministry of Health, policymakers can develop more targeted strategies for tackling ongoing and future pandemics.

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Received 29 October 2023; revised 9 May 2024; accepted 26 June 2024