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Assessing RTS, S malaria vaccine rollout perception in Cameroon: Sentiment analysis from X and facebook using hugging face

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Abstract

Background: The introduction of the RTS, S (Mosquirix®) malaria vaccine in Cameroon represents a significant public health milestone. This study analyzed social media sentiment surrounding the vaccine rollout using natural language processing and machine learning. **Methods:** Data from Twitter (X) and Facebook (Meta) regarding the RTS, S vaccine in Cameroon was analyzed using the Hugging Face Transformer library for sentiment evaluation. The data was pre-processed, cleaned, and visualized with Matplotlib. **Results:** The sentiment analysis revealed that 42.0% of reactions were negative, 40.0% were positive, and 18.0% were neutral, indicating a nearly even split between skeptical and supportive viewpoints among Cameroonian users regarding the vaccine rollout. **Conclusion:** The research highlights the necessity for targeted communication strategies to address public concerns and foster vaccine confidence. Sentiment analysis can act as a real-time tool, offering policymakers valuable insights into public reactions and attitudes toward immunization and other health initiatives. These findings reveal significant public skepticism that must be addressed through evidence-based communication strategies focused on vaccine safety, efficacy data from pilot programs, and engagement with community leaders to counter misinformation.

Keywords

artificial intelligence, hugging face, malaria vaccine, sentiment analysis, social media

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Background

Malaria remains a pressing public health challenge, particularly in sub-Saharan Africa. In 2022, the World Health Organization (WHO) estimated 249 million malaria cases globally, with sub-Saharan Africa accounting for over 94% of cases and 95% of deaths. Children under five remain especially vulnerable, representing approximately 80% of malaria-related deaths in the region.[1]

In Cameroon, malaria contributes significantly to illness, economic hardship, and school absenteeism. Annually, the country records over two million cases. Between 2016 and 2020, incidence rates increased from 79.5 to 120.2 cases per 1,000 population.[2]

Despite efforts to control malaria in Cameroon, incidence rates have steadily increased from 79.5 to 120.2 cases per 1,000 population between 2016 and 2020, highlighting the persistent threat and need for stronger interventions.[3] Achieving a malaria-free Africa remains challenging, notwithstanding global elimination efforts.[4] As of 2024, the WHO has certified only 43 countries worldwide as malaria-free, with just three from Africa: Mauritius, Algeria, and Cape Verde.[5] In response, Cameroon has implemented comprehensive control strategies, including the National Malaria Control Programme, government sensitization campaigns, and community outreach initiatives, all aimed at reducing the disease burden and progressing toward eventual elimination.[6]

In 2022, Cameroon launched phase one of its Universal Health Coverage (UHC) scheme, providing free malaria treatment for children aged 0-5 across all 10 regions with international partner support.[7] Building on this foundation, the 2024–2028 National Strategic Plan (CNSP) established ambitious targets for malaria reduction, aiming for a 75% decrease in morbidity, mortality, incidence, and transmission rates.[2] Despite these initiatives, malaria continues to pose a significant public health challenge.

The introduction of the RTS, S malaria vaccine,[8] recommended by the WHO in 2021, represents a promising advancement in the fight against malaria. The vaccine has proven effective in pilot programs across Ghana, Kenya, and Malawi, demonstrating a 30% reduction in severe cases.[9] Widespread implementation in high-transmission areas is essential for sustainable malaria control.

Cameroon made history in December 2022 as the first country to incorporate the RTS, S vaccine into its national immunization program.[10] However, this milestone has generated diverse public reactions, including vaccine hesitancy driven by misinformation and negative perceptions. Addressing these concerns is vital for achieving optimal vaccination coverage in Cameroon.[11,12]

Social media platforms like X and Facebook offer valuable windows into public sentiment regarding the vaccine rollout.[13] Sentiment analysis, which combines natural language processing (NLP) with machine learning, provides a powerful methodology for extracting meaningful insights from this data.[14] For this study, we employed the Hugging Face model,[15] which has previously demonstrated effectiveness in analyzing social media sentiments related to COVID-19[16] and climate change.[17]

Beyond COVID-19, sentiment analysis has proven valuable across various disease contexts. Research on malaria-related social media discourse in endemic regions has revealed community perceptions of prevention strategies and treatment accessibility.[18] During the 2014-2016 Ebola outbreak in West Africa, sentiment analysis of Twitter data helped public health authorities understand fear patterns and misinformation spread, informing targeted interventions.[19] Similarly, studies examining measles vaccination sentiments across multiple countries identified key drivers of vaccine hesitancy, including safety concerns and religious beliefs.[20] Research on HPV vaccine

acceptance in sub-Saharan Africa using social media sentiment analysis demonstrated how cultural factors and gender-specific concerns influenced vaccination attitudes.[21] These applications underscore sentiment analysis as a critical tool for understanding public health perceptions across diverse disease contexts and geographical settings, making it particularly relevant for assessing malaria vaccine acceptance in Cameroon.

Cameroon's health communication landscape presents unique challenges that influence vaccine-related discourse. The country's linguistic diversity (French and English as official languages, plus over 250 indigenous languages) creates complex communication dynamics where health messages may be interpreted differently across linguistic communities.[22] The dual health system common in Cameroon, combining biomedical and traditional healing practices, means that vaccine introduction occurs within a pluralistic medical environment where Western pharmaceutical interventions compete with traditional remedies for legitimacy.[23] Socioeconomic factors further complicate vaccine acceptance in Cameroon. With 37.5% of the population living below the poverty line and significant urban-rural disparities in healthcare access,[24] of concerns about vaccine costs (despite free provision), opportunity costs of clinic visits, and prioritization among competing health needs influence vaccination decisions. Additionally, the Anglophone crisis (ongoing since 2016) has created regional variations in trust toward government health initiatives, with populations in conflict-affected regions showing greater skepticism toward federal health programs.[25] Social media's role in Cameroon's health communication landscape has expanded rapidly; however, social media health discourse occurs within a context of widespread misinformation, limited health literacy, and influential traditional and religious leaders who may amplify or counter official health messages.[26] Previous research on HPV[27] and COVID-19[28] vaccine hesitancy in Cameroon identified safety concerns, religious objections, and mistrust of foreign pharmaceutical companies as primary barriers, factors that likely influence malaria vaccine acceptance as well.

Understanding sentiment toward the RTS, S vaccine rollout requires situating social media discourse within this complex landscape of linguistic diversity, historical mistrust, socioeconomic constraints, political tensions, and evolving digital communication patterns. This research, therefore, aims to evaluate Cameroonian users' perceptions of the RTS, S malaria vaccine rollout by analyzing data from Facebook and X. The findings will contribute to understanding public reception of this groundbreaking health initiative and inform targeted communication strategies to address concerns and promote vaccine acceptance.

Methods

Study design and objectives

This study employed a cross-sectional observational design to analyze public sentiment toward the RTS, S malaria vaccine rollout in Cameroon using social media data. Our primary objective was to quantify and characterize the sentiment distribution (positive, negative, neutral) among Cameroonian social media users discussing the vaccine. Secondary objectives included identifying temporal patterns in public engagement, extracting thematic content from sentiment categories, and assessing the relationship between official health communications and public response.

Methodological approach

We utilized a computational sentiment analysis framework combining natural language processing and machine learning techniques. The study analyzed publicly available data from two major social media platforms, X (formerly Twitter) and Facebook, over a defined period surrounding the vaccine introduction. Our methodological approach was designed to capture real-time public reactions while maintaining reproducibility through standardized data extraction, preprocessing, analysis, and visualization protocols. The workflow encompassed five sequential stages: data extraction, data storage, data preprocessing and transformation, data analysis, and data visualization.

Data extraction

Timeframe and sampling strategy. Data collection was conducted over 63 days from November 22, 2023, to January 25, 2024, strategically selected to capture public reactions during the initial rollout phase of the RTS, S malaria vaccine in Cameroon. This timeframe encompassed critical announcements by the Minister of Public Health and early implementation activities. We employed purposive sampling to identify relevant posts and replies containing keywords related to the malaria vaccine rollout in Cameroon, including terms such as "malaria vaccine," "RTS, S," "Mosquirix," "vaccination Cameroon," and their French equivalents ("vaccin paludisme," "vaccination Cameroun"). Our data collection strategy specifically focused on responses to official government health communications (primarily posts from the Minister of Public Health) rather than broader unsolicited public discourse about malaria vaccination. This methodological decision was deliberate and theoretically grounded. Research on health communication demonstrates that public responses to official government announcements provide critical insights into trust dynamics, perceived legitimacy of health authorities, and immediate reactions to policy implementation, factors that directly influence vaccine uptake.[29,30] Furthermore, government health communications serve as catalytic events that shape and concentrate public discussion, making responses to these posts particularly relevant for understanding how official information is received and contested. This approach aligns with previous social media studies examining vaccine acceptance in response to government communications during COVID-19 rollouts,[31,32] where official announcements served as focal points for public sentiment expression. We acknowledge that this approach captures reactive responses to specific communications rather than organic, unprompted discourse, and these have been addressed explicitly in our limitations section. However, for the specific research objective of understanding public reception of the official RTS, S vaccine rollout announcement in Cameroon, analyzing responses to ministerial communications provides direct insight into public-authority interactions during this critical implementation phase.

Platform-specific data collection. The workflow commenced with data collection from two key social media platforms, utilizing established APIs and libraries. For Facebook data extraction, we utilized the Graph API version 15.0 with the OAuth 2.0 authentication framework.[33] Data collection was conducted using Python 3.9.13 with the requests library (version 2.28.1) to make API calls with a rate limit of 200 requests per hour per user token. From Facebook, we extracted Post Source, Post Date, Post Content, and Post Replies. For X (formerly Twitter) data collection, we employed the Tweepy Python library version 4.14.0,[34] which interfaces with the Twitter API v2. Authentication was performed using Bearer Token authentication with elevated access

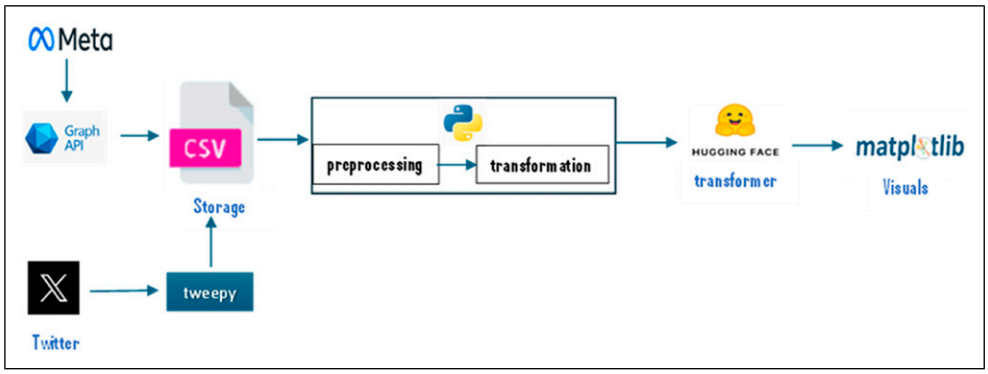

Figure 1. Workflow architecture.

permissions. The API rate limits were set at 450 requests per 15-min window for timeline queries and 900 requests per 15-min window for user lookup. From X, we extracted the following data: Tweet ID (stored in string format), Tweet Date (in ISO 8601 datetime format), Tweet Content (full text with extended mode enabled to capture tweets exceeding 140 characters), and Tweet Replies.

Workflow overview

Figure 1 depicts the methodology for the proposed social media data analysis workflow. The figure outlines a five-step process, starting with data extraction and ending with data visualization. Each step represents a critical stage in the data analysis workflow, utilizing specific tools and techniques to ensure the efficiency and effectiveness of the analysis. The following sections provide a detailed description of each step in the workflow, including complete technical specifications for reproducibility.

Storage of data

All extracted data was stored in CSV (Comma-Separated Values) format, which provided flexibility and compatibility with various data processing tools while facilitating seamless manipulation in subsequent workflow stages. Each CSV file was encoded in UTF-8 format to preserve multilingual characters from both English and French text. Each row represented an individual post or tweet, with columns corresponding to specific data attributes: source platform (categorical), date-time stamp (datetime64 format), content text (string), and reply text (string). Data files were stored locally with backup copies maintained on secure cloud storage (encrypted at rest) to ensure data integrity and prevent loss during analysis.

Data preprocessing and transformation

To ensure quality processing and maintain data integrity throughout the analysis pipeline, we implemented a systematic preprocessing and transformation framework using Python

3.9.13 with the Natural Language Toolkit (NLTK version 3.8.1). Quality assurance was ensured through three mechanisms: (1) validation checks at each preprocessing stage to verify data structure consistency and identify anomalies; (2) preservation of raw data backups before each transformation step to enable verification and rollback if needed; and (3) logging of all preprocessing operations with sample outputs for transparency and reproducibility. This rigorous preprocessing framework enabled the sentiment analysis tool to accurately interpret social media content without errors. Our data cleanup involved several systematic preprocessing steps. We first removed duplicates using pandas' drop_duplicates () function, reducing the dataset from 152 to 150 unique entries. Special characters, including emojis, hashtags, and URLs, were removed using regular expressions and the emoji library, while preserving semantic content where possible. Extra spaces, tabs, and newlines were normalized, and all text was converted to lowercase, except when case was needed for proper nouns in French. We also removed stop words using NLTK's English and French corpora, supplemented with social media–specific terms to retain sentence structure for sentiment analysis. Language detection was performed with langdetect, tagging entries as English, French, or mixed-language with a confidence threshold of 0.85. All preprocessing steps were implemented as a reproducible Python pipeline, with transformations logged for verification.

Data analysis

The pre-processed data underwent sentiment analysis using the Hugging Face Transformers library version 4.30.2 running on Python 3.9.13.[35] This powerful natural language processing framework facilitated sophisticated examination of social media text across all 150 rows of multilingual content in English and French. To address this linguistic diversity, we employed the cardiffnlp/twitter-roberta-base-sentiment-latest[36] multilingual model, which offered significant advantages, including high accuracy, strong performance in sentiment classification, and multilingual capability.[37] The analysis process was streamlined through the model's API, ensuring thorough and precise categorization of sentiments into three classes: positive, negative, and neutral. Through this implementation, we were able to extract meaningful insights from the data, providing a deeper understanding of user behavior and sentiment trends across these social media platforms.

Data visualization

Finally, the analysed data was visualized using the Matplotlib library.[38] This allowed for the clear and effective presentation of the results of the data analysis. The use of Matplotlib ensured that the results of the analysis were presented in a visually appealing and easily understandable format.

The pseudo-code was given as follows:

```
TextData: cleaned and preprocessed data
Procedure SentimentAnalysis (TextData)
Initialize the HuggingFace pipeline with the model
For each text in TextData do:
    Pass the text through the pipeline to get sentiment
    If sentiment is 'Positive' then
        Assign a label positive
    Else if sentiment is 'Negative' then
        Assign a label negative
    Else
        Assign a label neutral
    End if
    Store the label associated with the text
End for
Return the scores for all texts
End Procedure
```

Results

Descriptive analysis

The data collected consisted of 129 tweet replies from the period of 22nd November 2023 to 22nd January 2024, and 21 Facebook post replies spanning 23rd January 2024 to 25th January 2024. These data were collected from disparate sources, and the overall distribution of the combined data is depicted in Figure 2.

Sentiment analysis

Building on the descriptive analysis, we conducted sentiment analysis using the Hugging Face transformer model. To accurately interpret sentiments in both English and French replies, we employed appropriate multilingual models. The analysis revealed that 42.0% of tweets expressed negative sentiments toward the vaccine rollout, while 40.0% conveyed positive sentiments, and the remaining 18% maintained neutral positions.

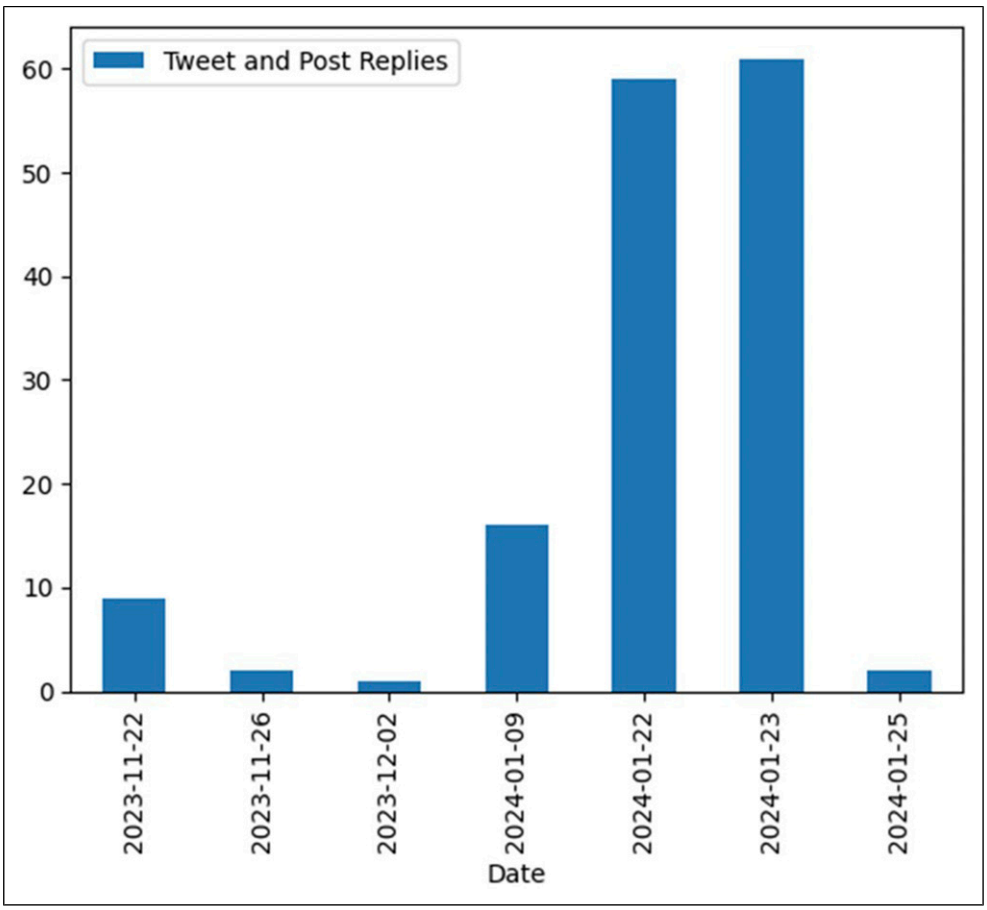

Figure 2. Distribution of the combined data.

The uncertainty surrounding sentiment proportions was estimated using 1,000 iterations of bootstrap resampling. For positive, negative, and neutral remarks, the 95% confidence intervals were roughly 45–53%, 35–43%, and 20–27%, respectively. The intervals show that positive sentiment is predominant in the sample, closely followed by negative sentiment, with neutral reactions making up a minority, despite the slight overlap. Despite the small sample size ($n \approx 150$), this offers a measure of robustness. Figure 3 below shows the distribution of sentiments across all analyzed comments, with 95% confidence intervals. Positive comments made up the majority of the sample (approximately 42%), followed by negative comments (approximately 38%) and neutral comments. The overlapping confidence intervals indicate that, while positive sentiment predominates, negative views account for a significant portion of the discussion. The relatively low proportion of neutral comments suggests that most users expressed emotionally charged reactions rather than impartial or factual statements.

To assess whether these sentiment distributions significantly differed from what might occur by chance, a Chi-squared goodness-of-fit test was conducted. This statistical method compares the observed sentiment frequencies to expected frequencies under the assumption of no preference (i.e., equal distribution). The test yielded a Chi-squared statistic of 0.0 with a p-value of 0.9, indicating no statistically significant difference between observed and expected sentiment categories. Although the Chi-squared test suggests no statistically significant difference in the distribution of sentiment categories, the observed data indicate that negative sentiment was the most frequently expressed (42%). This finding aligns with documented patterns of vaccine skepticism in Cameroon, where recent studies report COVID-19 vaccine hesitancy rates of 70.39%[39] and HPV vaccine concerns among 43% of healthcare workers in the Saa Health District.[40] While our Chi-squared test did not reach statistical significance ($p = 0.9$), likely due to our sample size of 150 responses, the

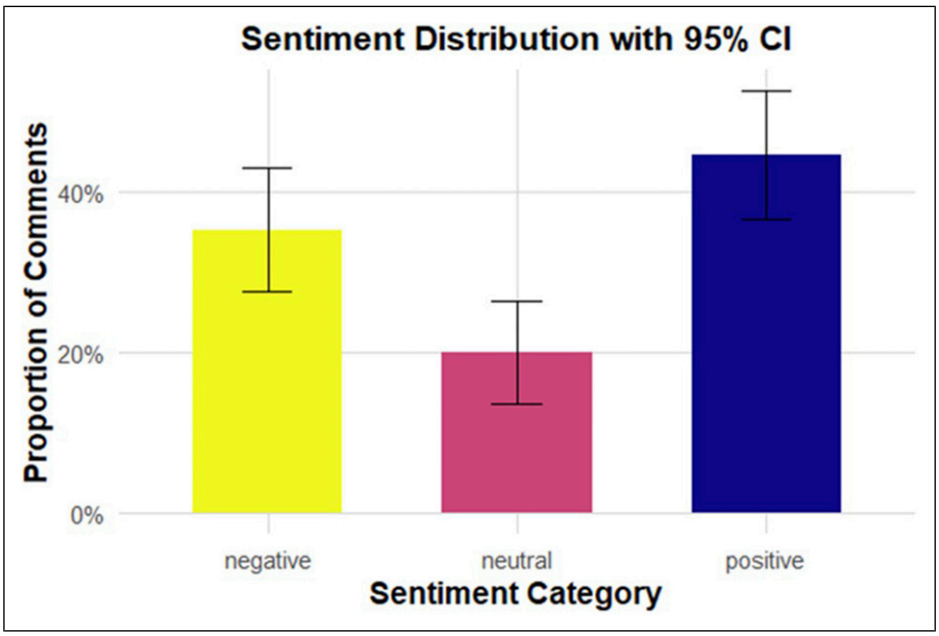

Figure 3. Distribution of sentiment polarities of replies.

observed 42% negative sentiment proportion falls within the range of documented vaccine hesitancy in comparable sub-Saharan African contexts.[41] Therefore, the sentiment analysis, supported by our qualitative themes and alignment with established hesitancy patterns in the region, highlights a meaningful inclination toward vaccine skepticism that warrants public health attention.

Density plot

In the multilingual sentiment model (cardiffnlp/twitter-xlm-roberta-base-sentiment-multilingual), each comment was assigned a probability for each sentiment label: positive, neutral, or negative. The density plot in Figure 4 visualizes these probabilities (i.e., the model's confidence) across the dataset. This visualization highlights where the model is most certain in assigning sentiment categories. A sharp peak near 1.0 indicates high confidence that comments belong to a specific class, whereas a flat or diffuse distribution suggests greater uncertainty or overlapping probabilities among classes.

The density distribution in the figure reveals that the model exhibits the highest confidence in negative classifications, with a pronounced peak between 0.8 and 1.0. Positive comments also cluster in the higher confidence range (0.7–1.0), though with lower density compared to the negative class. In contrast, neutral comments display a relatively uniform probability distribution, reflecting less distinct model confidence for this category.

This pattern indicates that negative sentiment within the dataset was both prevalent and lexically explicit, consistent with prior observations of public skepticism and critical tone in online vaccine discussions. The weaker and more diffuse confidence for positive comments likely reflects the subtler, less emotionally charged nature of supportive statements. Meanwhile, the flatter distribution for neutral comments may stem from the brevity and multilingual nature of the dataset, which can obscure affective nuances that monolingual sentiment models detect more effectively.

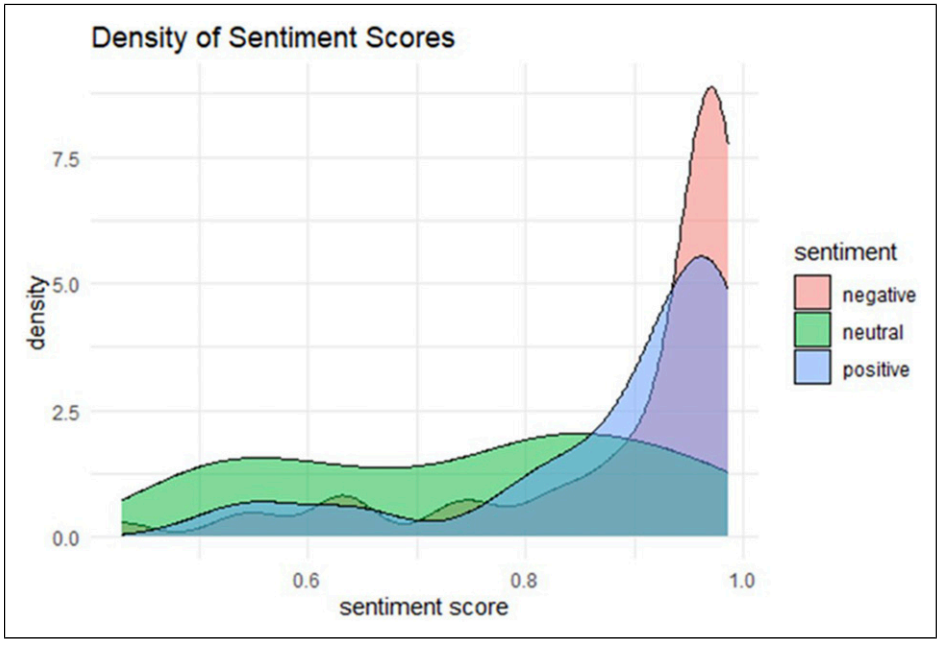

Figure 4. Density distribution of sentiment prediction probabilities across sentiment categories.

In summary, although positive comments were more common, negative comments were expressed more explicitly and with stronger lexical intensity, leading the model to assign them higher confidence scores. Positive expressions, by contrast, tended to be more nuanced or context-dependent, resulting in slightly lower confidence despite their greater frequency.

Thematic content analysis

Following sentiment classification, we systematically analyzed all 150 responses to identify recurring themes within each sentiment category, informed by word cloud visualization (Figure 5). We identified themes based on: (1) frequency of similar concerns across multiple responses, (2) linguistic markers (Francophone vs Anglophone expressions, Cameroonian idioms), and (3) socio-economic references (healthcare costs, disease priorities, resource allocation). Representative quotes

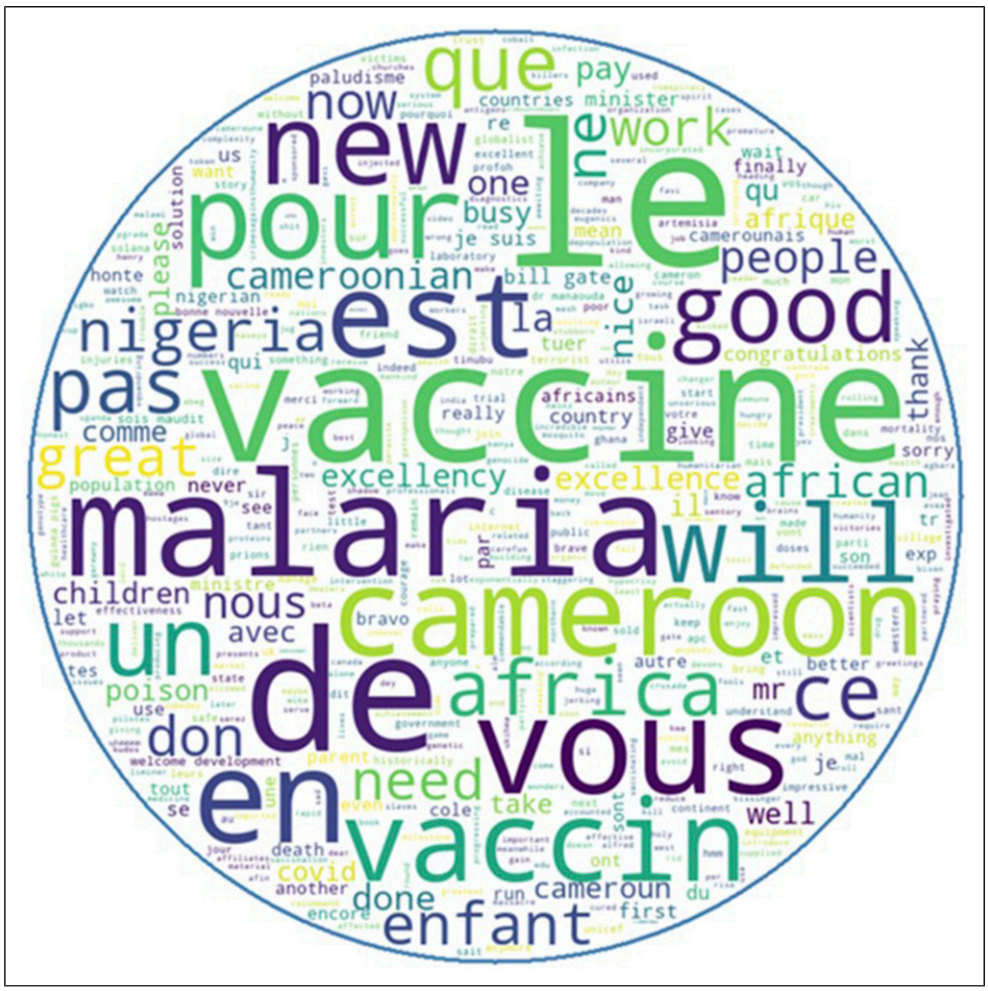

Figure 5. Word cloud of the data.

were selected to illustrate patterns observed across multiple responses within each theme, not isolated opinions.

Figure 5 presents a word cloud visualization of the most prevalent terms for each sentiment polarity. By extracting relevant codes from these word clouds, we enriched our thematic analysis, gaining deeper insights into sentiment patterns within the user-generated content. These extracted codes were subsequently categorized according to their association with positive, negative, or neutral sentiments.

At the document level, sentiment analysis classifies opinions as either positive or negative, interpreting the sentiment of the entire text as a unified whole.[42,43] Two major methodological approaches are commonly applied at this level: supervised and unsupervised learning. In supervised learning, documents are categorized into predefined classes using labeled training data to determine their overall polarity. Conversely, unsupervised methods rely on semantic orientation, estimating the sentiment of a document by analyzing the polarity strength of specific words or phrases it contains. If the average semantic orientation exceeds a set threshold, the document is labeled positive; otherwise, it is classified as negative.[44]

Positive sentiments (40.0%). Positive sentiments reflected three themes: (1) recognition of malaria's disease burden and child mortality impact (socioeconomic concerns about healthcare costs), (2) support for public health advancement (cultural values of collective improvement), and (3) optimism about child health outcomes (parental protection motivations).

A substantial portion of the public expressed optimism regarding the malaria vaccine rollout, underscoring its perceived importance of vaccination in reducing malaria cases and related deaths. Words and phrases such as "Good work," "Great job," "Congratulations on the new vaccine," "Excellence in malaria prevention," and "A better future for African children" suggested positive reactions to the vaccine rollout. These terms reflect a strong appreciation for the potential impact of the malaria vaccine, with users recognizing its significance in reducing the disease burden and celebrating the vaccine's introduction.

These positive sentiments are largely connected to the vaccine's potential to address a long-standing health crisis, with users acknowledging both malaria's historical significance and the promising advancements in public health interventions. The messaging around the vaccine's benefits resonated with a significant segment of the population, particularly those who recognized it as a critical tool in global malaria eradication efforts. For example:

> *"According to WHO, the African continent accounted for approximately 94% of global malaria cases and 95% of related deaths in 2022. Rapid diagnostics, better treatments, and vaccines are very important to achieve one of the greatest humanitarian victories of our time: end malaria.* (Positive Facebook quote)

Another comment from an X user was:

> *"This is great news. Historically speaking, malaria has been one of the worst killers known to mankind.* (Positive X quote)

These comments reflect an alignment with the public health narrative that positions the malaria vaccine as a key component of reducing the disease burden and achieving significant health milestones.

Negative sentiments (42.0%). Negative sentiments also revealed three main themes: (1) safety concerns linked to previous vaccine experiences, particularly the yellow fever vaccine, (2) competing health priorities arguing HIV deserved greater attention, reflecting socioeconomic calculations about disease burden; and (3) pharmaceutical mistrust invoking colonial exploitation narratives, reflecting historical medical mistrust.

Despite widespread positive reactions, a slightly higher percentage of users expressed concerns or skepticism about the vaccine. Comments containing phrases such as "poison," "The minister should be held accountable," "This vaccine is poison," "We don't need this," and "Pas de solution" (No solution) indicated significant concerns regarding the vaccine's safety and efficacy. These expressions highlighted distrust and frustration, particularly toward authorities promoting the vaccine. Many users believed other health priorities existed or questioned whether the vaccine would deliver its advertised benefits, revealing underlying concerns about safety, leadership mistrust, and unmet health needs.

These negative sentiments primarily stemmed from mistrust in vaccination processes generally, fears about potential side effects, or beliefs that other diseases, particularly HIV, deserved higher priority than malaria. Some comments reflected frustrations with previous negative vaccine experiences, which fueled hesitation or outright opposition.

One Facebook user expressed:

> *"Mr. Minister, please, if that little girl is not restored from the yellow fever vaccine which you recommended and handed to the parents in her initial state, then just keep these other vaccines for you and your family. Thank you.* (Negative Facebook Quote)

An X user similarly demanded:

> *"We want a vaccine for HIV, not malaria.* (Negative X Quote)

These responses reveal noteworthy challenges in vaccine acceptance, as many individuals felt that the rollout failed to address their most pressing health concerns or triggered anxieties stemming from previous negative experiences with vaccines.

Neutral sentiments (18.0%). Neutral responses showed two patterns: (1) factual information sharing within social networks, and (2) reserved wait-and-see attitudes using culturally-specific phrases like "we shall see", Cameroonian communication norms maintaining courtesy while reserving judgment.

The neutral comments were predominantly observational, typically sharing factual information or updates about the vaccine rollout without expressing strong personal opinions.

Common phrases included *"New vaccine in Cameroon," "Malaria vaccine rollout in Africa," "Excellency announced the vaccine," and "Children receiving vaccines."*

These comments focused primarily on factual context rather than conveying strong feelings for or against the initiative. While not indicating specific stances, they contributed meaningfully to the broader discussion around the vaccine's introduction and public health significance.

Although these neutral sentiments provided less insight into public opinion than their positive and negative counterparts, they played an important role in shaping the overall conversation about the vaccine rollout.

Many simply conveyed information or news updates, as illustrated by this Facebook comment:

"The new malaria vaccine has been introduced in Cameroon. It's good to see steps being taken to fight this disease, but it will take time to see how effective it really is, especially in children" (Facebook Neutral Quote)

An X user, in the same way, noted:

"Malaria vaccine just launched in Cameroon. Hope it makes a difference." (X Neutral Quote)

These neutral perspectives helped establish the factual foundation upon which more opinionated discussions could develop, creating a more complete picture of public discourse surrounding the malaria vaccine initiative.

Discussion

The bar chart in Figure 2 vividly illustrates the public's response to the tweets concerning the malaria vaccine. The highest peaks in the data were observed on January 23, 2024, and January 22, 2024. These peaks corresponded to the dates when the Minister of Public Health made tweets about the malaria vaccine. These considerable peaks indicated a substantial increase in replies to the Minister's tweets, suggesting that these official communications ignited significant public interest and sparked active discussion around the malaria vaccine introduction. The heightened activity during these periods could be attributed to the authoritative nature of the source and the perceived importance of the information being disseminated, providing empirical evidence of how government communications drive social media discourse, a pattern not previously documented for malaria vaccine introduction. This finding has practical implications for the timing and frequency of official health communications. This observation also underscores the influential role that prominent public figures and official sources play in shaping public discourse and generating widespread attention, both supportive and critical, towards public health initiatives. Regular and transparent updates from health officials can significantly influence public sentiment and engagement. The spikes suggest that people are eager for information and reassurances from trusted sources. Additionally, the high level of replies indicates a demand for interactive communication where the public feels heard and can receive timely responses to their queries. This interaction can help build trust and address misinformation more effectively.

For example, a study on the Chinese government's use of WeChat to disseminate information about COVID-19 found substantial public interaction with the official accounts, highlighting how social media can serve as an effective tool for public communication and engagement in health initiatives.[45] Similar research conducted in Switzerland on COVID-19 discussions among scientists, policymakers, and media through Twitter interactions and public opinion surveys found that health experts and politicians interact differently in pandemic communication, though there was little correlation between online engagement and trust.[46]

Monitoring such spikes in engagement levels can aid in identifying opportune moments for targeted communication strategies and proactively addressing concerns or misconceptions that may arise within the public sphere.

It is also worth noting the distribution of replies over time. The bar chart in Figure 2 shows fluctuations in reply numbers, with certain dates seeing more activity than others. This could be attributed to various factors such as the content of the tweets, the time they were posted, and the prevailing public sentiment on those dates.

The sentiment analysis results from this study revealed that public sentiment regarding the RTS, S malaria vaccine in Cameroon is balanced, with neither positive (42%), negative (18%), nor neutral (42%) sentiments dominating the discourse. There could be several possible reasons for the negative sentiments observed. First, vaccine hesitancy and skepticism towards new medical interventions are not uncommon, particularly in developing countries like Cameroon. Past experiences with ineffective or harmful medical treatments, coupled with widespread misinformation and rumors, can fuel distrust in public health initiatives.[47]

Our results more closely align with Vishwakarma and Chugh 's analysis of COVID-19 vaccination sentiment in India, which revealed mixed attitudes with substantial vaccine hesitancy despite overall positive trends.[48]

Additionally, concerns about the safety and efficacy of the RTS, S vaccine may have played a role in shaping negative perceptions, particularly as the vaccine is designed for children. Despite its endorsement by the WHO, some individuals or groups might harbor doubts about the vaccine's ability to provide adequate protection against malaria or about potential side effects.[49,50]

Furthermore, socio-cultural factors and religious beliefs could have influenced the public's perception of the vaccine rollout. In certain communities, traditional practices or beliefs may clash with modern medical interventions, leading to resistance or skepticism. There were also grievances suggesting that the vaccine is merely a profit-making strategy for certain Western pharmaceutical corporations.[51,52]

Importantly, our study represents the first sentiment analysis of malaria vaccine acceptance in Central Africa, addressing a critical gap in the literature. Previous malaria-related social media research has focused primarily on treatment-seeking behavior and prevention strategies[53–55] rather than vaccine acceptance. The balanced sentiment distribution we observed (42% negative, 40% positive) suggests that malaria vaccine introduction faces different acceptance dynamics than COVID-19 vaccines, potentially due to malaria's endemic nature versus the acute pandemic crisis that drove COVID-19 vaccination urgency.

The results of this study align with findings from a sentiment analysis of Twitter data from India, which revealed a predominantly positive attitude toward COVID-19 vaccination, despite some negative sentiments related to vaccine hesitancy, side effects, and mistrust.[56]

However, a sentiment analysis study toward the COVID-19 vaccine in Argentina, Chile, Colombia, Mexico, and Peru revealed mostly negative sentiments, with positivity only appearing at the beginning of the pandemic.[57] Contrary to our findings, a sentiment analysis study of COVID-19 vaccination on Twitter by Yousefinaghani et al.,[58] recorded predominantly positive sentiments.

The positive sentiment of 42% in our study indicates that a notable segment of the population recognizes the potential benefits of the malaria vaccine and supports its introduction. This finding may reflect varying levels of awareness and trust in public health initiatives, suggesting the need for more targeted communication strategies. Additionally, this sentiment may be influenced by individuals' varying experiences with malaria, highlighting the importance of addressing trust issues in public health messaging to enhance community engagement and vaccine acceptance.

While a significant portion of responses on social media expressed support or optimism, it is important to note that this may not fully represent the general population, as internet access and social media usage are not uniformly distributed across Cameroon. Therefore, the findings should be interpreted with caution, considering the potential for selection bias.

Meanwhile, 42% of the sentiments were neutral, suggesting an impartial or indifferent stance towards the tweets. Some of the replies were factual, questioning, or simply acknowledging the information without expressing a clear positive or negative sentiment.

Methodologically, our study demonstrates the feasibility and value of using transformer-based multilingual sentiment analysis in resource-limited settings with multiple official languages. The successful application of the cardiffnlp/twitter-roberta-base-sentiment-latest model to simultaneous English and French content provides a replicable framework for other multilingual African countries implementing health interventions.

Looking forward, emerging technologies offer promising avenues for advancing social media health sentiment research. Federated learning approaches could enable privacy-preserving distributed analysis across multiple African countries' social media platforms, allowing cross-national vaccine sentiment comparisons without centralizing sensitive data, a critical advancement given privacy concerns in health data analysis.[59] Additionally, sophisticated neural network models capable of detecting authentic versus deceptive communication patterns[60] could be adapted to distinguish genuine user opinions from manufactured content (such as bot-generated posts or coordinated campaigns) in health discourse, thereby providing more accurate representations of true public sentiment. Future research may also consider employing longitudinal designs tracking sentiment evolution beyond initial rollout phases, integrating real-time monitoring systems for health authorities to identify misinformation spikes, and conducting cross-cultural comparative studies as other African countries introduce the RTS, S vaccine to illuminate generalizable versus context-specific acceptance factors.

Moreover, to gain a more comprehensive understanding of the reasons behind the observed sentiments, it would be beneficial to complement this sentiment analysis with qualitative research methods, such as focus group discussions or in-depth interviews with individuals expressing varying sentiments. This could uncover nuanced perspectives, cultural factors, or specific concerns that could inform targeted interventions and communication strategies to address vaccine hesitancy and promote acceptance of the RTS, S malaria vaccine in Cameroon.

Conclusion

This sentiment analysis study reveals a complex and divided public perception of the RTS, S malaria vaccine rollout in Cameroon. While 40.0% of sentiments were positive, indicating optimism and acceptance of the vaccine, a slightly higher proportion (42.0%) expressed skepticism and concern. This reflects the multifaceted barriers to vaccine acceptance, such as mistrust, safety concerns, and cultural perceptions. The results underscore the urgent need for communication strategies specifically designed for the Cameroonian context and address the three main concerns identified in our analysis: (1) vaccine safety fears, by disseminating clear, evidence-based data from the pilot programs in Ghana, Kenya, and Malawi showing the vaccine's safety profile; (2) the perception that HIV deserves higher priority than malaria, by emphasizing that malaria causes over two million cases annually in Cameroon and that multiple health priorities can be addressed simultaneously; and (3) distrust stemming from previous negative vaccine experiences, by engaging trusted community leaders, religious authorities, and local health workers who can provide culturally sensitive messaging and address misinformation. Proactive engagement through community dialogues, transparent reporting of vaccination outcomes, and responsive communication from health officials will be essential in boosting vaccine confidence and ensuring the successful nationwide implementation of the RTS, S vaccine in Cameroon.

Recommendation

Addressing the negative sentiments requires a multifaceted approach, such as strengthening communication strategies to provide clear, accurate, and culturally sensitive information about the vaccine. In addition, building trust by engaging with local communities and leveraging successful vaccination stories can empower others to get their kids vaccinated.

It is highly recommended that future research continue to monitor public sentiment over time and evaluate the impact of targeted interventions aimed at improving public perception and vaccine uptake. Understanding and addressing the root causes of negative sentiment is crucial for the successful implementation of the RTS, S malaria vaccine, and other public health initiatives in Cameroon and beyond.

Strengths and limitations

Strengths

This study stands out as a pioneering effort in Cameroon and the broader Central African region, introducing an innovative application of artificial intelligence and natural language processing to assess public sentiment surrounding the RTS, S malaria vaccine rollout. By leveraging the Hugging Face Transformer library, the study successfully analyzed multilingual data from both English and French sources, reflecting Cameroon's complex linguistic environment and ensuring a more inclusive understanding of public opinion. This methodological innovation demonstrates the feasibility of using advanced AI models for real-time health communication monitoring in resource-limited and multilingual contexts, offering a replicable framework for other African countries introducing similar public health interventions. Beyond its technical sophistication, the study provides timely, policy-relevant insights that can inform targeted communication strategies, strengthen public trust, and improve vaccine acceptance. It also contributes to the emerging field of digital epidemiology by showcasing how social media analytics can serve as a low-cost, scalable, and responsive tool for gauging community reactions to health innovations. Collectively, these strengths highlight the study's originality, methodological rigor, and practical relevance in advancing both scientific understanding and evidence-based public health policymaking.

Limitations

This study has several specific limitations that must be acknowledged. First, a potential systematic selection bias likely occurred due to our data collection method. The survey was distributed via social media platforms (X and Facebook), and participation required internet access and digital literacy. We did not compute a numerical bias coefficient; however, the demographic characteristics of respondents, primarily younger, urban, and university-educated individuals, indicate a systematic overrepresentation of digitally connected populations and underrepresentation of rural, older, and less educated groups. This inference is based on national statistics showing that less than 40% of Cameroonians have regular internet access. Consequently, our sample is not fully representative of the general population.[61]

Secondly, the demographic composition of X and Facebook users in Cameroon skews toward more educated and wealthier individuals, limiting the generalizability of the findings beyond this subgroup. Our sample size of 150 responses, while successfully capturing the diversity of sentiments and thematic patterns, limited our statistical power to detect significant differences between

sentiment categories. Post-hoc power analysis revealed that with 150 responses and the observed sentiment distribution (42% negative, 40% positive, 18% neutral), our study achieved only 28% statistical power to detect differences at $\alpha = 0.05$, well below the conventional 80% threshold. This explains why our Chi-squared test yielded a non-significant result ($p = 0.9$) despite observing a numerical difference between sentiment categories. Approximately 385 responses would have been required to achieve the conventional 80% power for meaningful comparisons.[62]

Thirdly, the sentiment analysis algorithms used may not fully capture linguistic subtleties or context-specific meanings, particularly in Cameroon's multilingual setting, where code-switching and cultural expressions can alter sentiment interpretation.

Lastly, the sentiments analyzed were derived from reactions to specific posts on vaccine rollout rather than general opinions about COVID-19 vaccination, limiting broader inference. Future research should therefore utilize larger, more demographically diverse samples and integrate multiple data collection methods (e.g., offline surveys) to validate and extend these findings.

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Ethical considerations

There are no human participants in this article, and informed consent is not required. However, in collecting Twitter and Facebook data for sentiment analysis, strict adherence was maintained to each platform's terms of service and ethical guidelines. Following recent changes in Twitter's policies, data access required the creation of a developer account and the purchase of an access token. This ensured full compliance with Twitter's API usage policies, which are designed to prevent unauthorized data scraping. While this paid access introduces potential barriers to data accessibility, careful steps were taken to ensure that data collection methods were transparent, responsible, and aligned with the ethical standards of digital research. Additionally, consideration was given to the ethical implications of financial barriers, with advocacy for equitable access to public data for research purposes.

Authors' contributions

ANC initiated the project and wrote the manuscript. MN and NZF collected the data and performed the analysis. NK assisted in writing the manuscript. All authors reviewed the final manuscript draft.

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Data Availability Statement

Data will be provided upon request.

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Appendix

List of abbreviations

NLP	Natural Language Processing
WHO	World Health Organization
UHC	Universal Health Coverage
SSA	Sub-Saharan Africa
NMCP	National Malaria Control Programme
PMI	Presidential Malaria Initiative
CNSP	Cameroon National Strategic Plan
NGO	Non-Governmental Organization
CSO	Civil Society Organization
ITNs	Insecticide-Treated Nets