What about Language? A Multilingual Behavioural Study of User Engagement with Disinformation on X

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Abstract

Research into user engagement with disinformation has grown rapidly, identifying factors like emotion, credibility, and content structure. Yet, how linguistic and cultural identity shape engagement remains understudied. This study fills this gap by exploring the dynamics of language and user engagement with disinformation in a multilingual online context. Using a data-set of more than 5,000 disinformation tweets about the human papilloma virus (HPV) vaccine in 30 languages, the analysis investigates the interaction between language, sentiment, and topical themes in shaping engagement with disinformation through metrics such as likes, retweets, quotes, shares, and replies. The regression, sentiment and topic modelling results reveal language-specific trends and cultural and contextual nuances. For example, tweets in Swedish show a strong positive correlation between sentiment and engagement, while German tweets display negative correlations for certain topics, such as vaccine efficacy. These findings indicate that the experience of disinformation is not universal and underscore the importance of analysing it through a multilingual and multicultural lens. The paper ends by offering actionable insights for practitioners and researchers to improve the understanding of cultural dynamics in global communication, advancing methods to combat online disinformation in complex, multilingual environments such as social media platforms.

Keywords

Disinformation, Cultural Influence, Multilingual Analysis, Engagement behaviour

1. Introduction

Online disinformation—intentionally disseminated false or misleading content causing public harm [1]—has surged in recent years, especially after the COVID-19 health crisis. Recognized as a major threat to personal and public safety, particularly in health, extensive research has focused on analyzing the structure [2, 3], spread [4], impact [5, 6, 7], and content [8, 9, 10] of disinformation, including conspiracy theories and fake news, and the consequences of health-related misperceptions on behaviour [11, 12]. Scholars have also examined user interaction and network structure's impact on disinformation spread [13, 14] and features through which disinformation persuades individuals [15, 16, 17]. However, despite rapid growth, the fundamental reasons individuals engage with disinformation remain unclear. Scholars attribute this uncertainty to fragmented findings and a tendency to see disinformation merely as the opposite of truth, neglecting its cognitive and subjective aspects [18, 15, 19, 16, 20]. While both arguments are valid, this study argues that a key gap in the literature is the lack of research addressing the role of culture and language in driving engagement with disinformation.

This argument is supported by at least two factors. First, most current research focuses disproportionately on a small number of advanced democracies like the United States and the United Kingdom [21]. A study by Seo & Faris [22] found that 62.8 percent of empirical articles published in communication journals between 2015 and 2020 used data from the U.S. Authors like Bajaj [21] argue that disinformation is not experienced universally, and this geographic bias distorts our understanding of disinformation and undermines mitigation efforts that ignore cultural dynamics.

Second, specific cultural groups are often targeted by coordinated disinformation campaigns [23].

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For example, research found that Russian disinformation campaigns on X exploit racial and political identities to infiltrate online communities with politically charged content [24]. Disinformation also reaches cultural groups through direct messages. Studies show that WhatsApp disinformation targeted South Asian voters in North Carolina, while mistranslated content about Joe Biden targeted Spanish-speaking voters in the U.S. [25].

The global complexity of the digital communication landscape highlights the need to understand how different cultural and linguistic groups are susceptible to disinformation. This study aims to address this gap by investigating the role of linguistic and cultural identity in shaping disinformation experiences. Using a data-set of 5,183 disinformation tweets in 30 languages, the study employs regression analysis, sentiment analysis, and topic modelling to examine the relationship between language, sentiment, and topical themes in shaping user engagement with disinformation. The results emphasize the significant influence of linguistic and cultural factors in shaping individuals' susceptibility to disinformation, providing a more nuanced perspective on how people engage with disinformation across multilingual contexts.

2. User engagement and disinformation

The literature on user engagement in online contexts has explored this phenomenon through various frameworks and methodologies. Engagement is often defined as user-initiated actions that contribute to the co-creation of value, as posited by Brodie et al. [26]. This broad definition captures the interplay of behavioural, cognitive, and emotional dimensions, emphasizing the need to explore interaction nuances and motivations. Shao [27] categorized user interaction into three behaviours: consumption (viewing), participation (interacting), and production (creating content). Several studies have further differentiated between active participation (e.g., liking, commenting, sharing) and passive consumption (e.g., clicking, watching) [28, 29], particularly on platforms like Facebook, YouTube, and X (formerly Twitter) [30]. Although passive users, or 'lurkers', comprise up to 90% of online communities [31, 32], a smaller active subset significantly shapes the content landscape.

Recent research has examined the factors driving user engagement with disinformation. Emotionally charged content, including sensationalized headlines and narratives, has been found to amplify engagement by exploiting emotions like fear and anger [33]. Visual elements and features like clickbait and references to specific entities also enhance perceived credibility and emotional resonance, driving engagement [34, 35]. Other factors, such as source credibility, social media fatigue, and fear of missing out, have been found to influence the sharing of fake news [36, 37], designed to grab attention and provoke emotions.

The role of content creators in spreading disinformation is also significant [38]. Audiences trust content from credible sources, with attributes like platform tenure, audience size, and verified profiles increasing perceived credibility [39, 40]. Emotionally charged content from trusted sources, particularly those with large followings, amplifies the spread of disinformation [41, 42].

This study builds on this literature, proposing that language and culture are central to disinformation's ability to leverage emotion and drive engagement. The hypothesis is that subjective emotions like fear and anger are shaped by one's culture, values, and experiences [18]. While digital platforms have amplified these emotions [4, 43], attributing them solely to technology oversimplifies the issue [44]. Disinformation has existed long before the internet, and factors like individual traits, cultural beliefs, personality, education, and sociopolitical contexts such as populism and distrust in expertise also play a role [45, 46]. Disinformation content must therefore resonate with audience values and enhance the virality of its messages. For instance, research links conspiracy theories and cultural stereotypes with the spread of fake news and hate speech [18, 47, 6, 48]. This study underscores the importance of understanding linguistic and cultural dynamics in crafting strategies to combat disinformation and protect public discourse. By examining the relationship between language, sentiment, and topical themes, the results will offer data-driven empirical evidence that highlights the critical role of linguistic and cultural factors in shaping engagement.

3. The HPV vaccine and disinformation

In recent years, particularly following the COVID-19 health crisis, health-related disinformation has surged globally, becoming one of the most significant threats to public well-being. Vaccine hesitancy, historically influenced by time, location, and type of vaccine, was notably intensified by the 2020 pandemic [49, 44]. A key example of the intersection between disinformation and vaccine hesitancy is the human papillomavirus (HPV) vaccine Gardasil, licensed by Merck in 2006 [12, 50].

HPV, the most common sexually transmitted infection globally, includes over 100 strains, with an estimated 80%-90% of individuals contracting it at some point [51]. Of these, 13 are oncogenic, with cervical cancer being the most common HPV-related cancer, and the fourth most common cancer in women worldwide [52, 53]. The vaccine, initially approved only for females aged 9 to 26, led to the "feminization" of HPV, intertwining the vaccine with issues of gender norms and sexuality, including perceptions of female virginity and promiscuity [54, 55, 56]. This focus overlooked men, especially those who have sex with men, which exposed heteronormative biases [56]. By 2022, 125 countries had included the vaccine in routine programs for girls, compared to only 47 for boys [57], perpetuating misconceptions that HPV is solely a women's issue and leaving men less protected.

The feminization of HPV has made Gardasil a target for anti-vaccine disinformation. Since 2006, critics have raised concerns about promiscuity, incomplete protection, mandatory vaccination, health disparities, and unreported adverse effects [58, 11, 59]. These concerns have been amplified through social media and propaganda films like Andi Reiss's 2018 documentary *Sacrificial Virgins: Not for the Greater Good*, which claims the vaccine caused paralysis in two girls. The film sparked controversy in Australia, leading to an attempted ban on its distribution [60]. Other disinformation materials include *The HPV Vaccine on Trial: Seeking Justice for a Generation Betrayed* [61] and a now-retracted article suggesting the vaccine reduces fertility [62].

Conspiracy theories surrounding the HPV vaccine have also flourished, blending science, politics, economics, and gender. In China, for example, some claim the vaccine is a profit-driven tool or a Western bioweapon targeting the Chinese population [11]. Broader conspiracies accuse governments and pharmaceutical companies of fabricating vaccine data, claiming infertility or ovarian insufficiency, or asserting the vaccine is part of a depopulation agenda [49, 63]. These narratives have fueled public mistrust in health authorities and created a fertile environment for disinformation. Given the global circulation of these narratives, understanding how different users engage with and respond to disinformation narratives—especially those shaped by cultural and nation-specific contexts—becomes crucial for analysing disinformation.

4. Data and methodology

The data-set covers a total duration of 394 days spanning a time period from 1 August 2022 to 30 August 2023. It contains 5,183 tweets in 30 languages and several attributes such as the tweet texts, the hashtags, likes, replies, retweets, shares, and quotes count. A description of the data-set is given in Table 3 in the Appendix. Data retrieval was conducted through targeted queries that extracted tweets containing specific hashtags, including *#HPV*, *#papillomavirus*, and *#Gardasil*. To isolate disinformation content, qualitative and quantitative analyses identified frequent additional hashtags, primarily *#Agenda2030*, followed by *#The GreatReset* and *#NewWorldOrder*. Other commonly used hashtags were *#ProtegeonsNosEnfants* (*let's protect our children*), *#nonsonovaccini* (*they are not vaccines*), *#VaccineAdverseEffects*, *#VaccineDeaths*. The full list of hashtags is provided in 4 in the Appendix. These hashtags, identified as being associated with disinformation, fake news, and conspiracy theories [64, 65, 66], were selected as the basis for the working data-set. The data-set was pseudomysed to remove any identifiable references and it can be provided upon request to the author.

This study suggests that the behavioural analysis of user engagement with the selected posts offers quantifiable measures of disinformation dissemination and reception. Engagement is here defined as the sum of likes, shares, retweets, quotes, and replies given to each tweet, as discussed earlier in the paper. The study assumes that these metrics will indicate the interaction, endorsement and general dissemination of the audience. After calculating users' engagement, the analysis proceeds with computing Latent Dirichlet Allocation (LDA) topic modelling (TM) [67] of the tweets' content. TM is a computational, statistical method to discover linguistic patterns in large collections of texts. Based on distributional semantics theory [68], TM assumes that groups of words purport collective meanings, i.e., *topics*. By calculating the correlation between topic contributions as derived from the LDA model and engagement, the analysis will determine the relationship between specific topics and how audiences engage with content. Next, sentiment analysis is applied to the topics and the correlation between sentiment and engagement is calculated. The aim is to examine whether the tone (positive, negative, or neutral sentiment) of topics as derived from the tweets influences how audiences interact with them. Finally, a comprehensive analysis of the relationships between language, sentiment, engagement, and topics is calculated from the overall correlations and language-specific correlations to understand how engagement behaviours vary across languages and topics.

5. Analysis and results

5.1. Preliminary observations

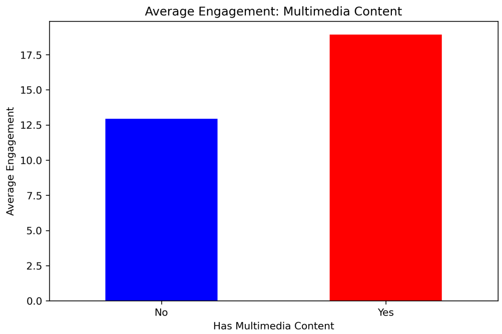
Before proceeding to the analysis of the correlation between topics and users' engagement, it is worth examining whether there is a statistically significant difference in the average engagement for tweets across various features, such as multimedia content, verified user status, hashtags, and mentions. This helps identify patterns in how specific features impact the overall engagement. In turn, this analysis provides an initial overview of users' behaviour on X. Figures 1-4 show the results. Notable insights are already emerging. In this analysis, a two-sample independent t-test was conducted for which tweets were grouped based on the presence or absence of these specific features.

For each feature, the T-test returned the size of the difference relative to the variation in engagement values whereas the p-value determined the statistical significance of the difference below the significance level of 0.05. The results show that tweets with multimedia content (e.g., images, videos, links) have substantially higher average engagement (p-value=0.03 significant at the 0.05 level) (see 1a), confirming that visual or interactive elements drive audience interaction. On the other hand, the use of hashtags does not significantly affect engagement levels. In fact, engagement is slightly lower for tweets with hashtags, suggesting that hashtags alone are not strong drivers of interaction in this data-set (see 1b). Similarly, tweets with mentions do not significantly differ in engagement from those without mentions. Again, engagement is marginally lower for tweets with mentions, which may reflect limited audience interest in direct interactions (see 1c). Finally, tweets by verified users generate dramatically higher engagement, likely due to their perceived credibility, larger follower base, or higher visibility in algorithms, as found in the literature and previously discussed here (see 1d). An overview of the regression analysis results is provided in Table 2 in the Appendix.

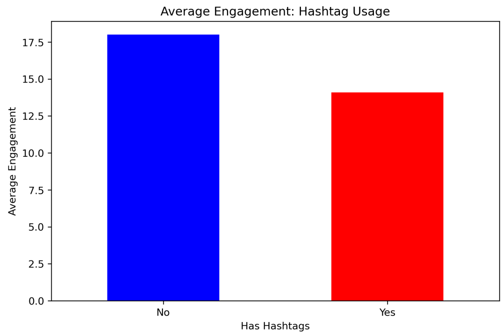
5.2. Topic modelling and engagement

This part of the analysis applies LDA on the tweets' content and calculates the correlation between topic contributions and engagement to determine the relationship between specific topics and how audiences engage with content. LDA was implemented using the LdaModel class from the Gensim library. The optimal number of topics `best_num_topics` was determined empirically using coherence scoring for higher interpretability and topic quality. Coherence scores were calculated across models with 2 to 10 topics (see 2a). Based on the results, the 5-topic model was selected for analysis, as it achieved the highest coherence score (0.5419), indicating the best balance between granularity and interpretability. The 5-topic model was then trained on a bag-of-words representation of the tweets (corpus), with a fixed random seed (`random_state=42`) to ensure reproducibility.

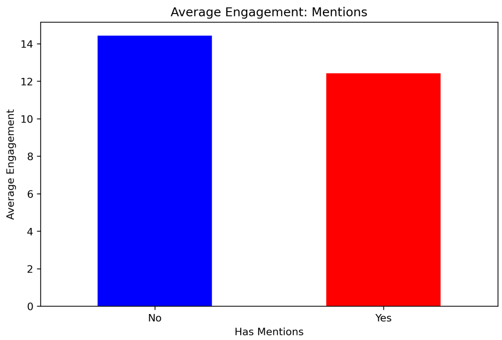
Model training employed an online variational Bayes algorithm with the `update_every` parameter set to 1, enabling incremental updates after each mini-batch of size 100 (chunksize=100). A total of 10



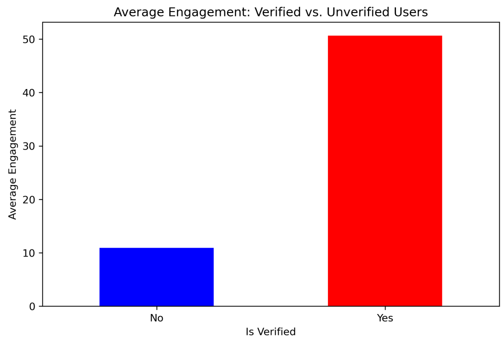
(a) Tweets with media content



(b) Tweets with hashtags



(c) Tweets with mentions

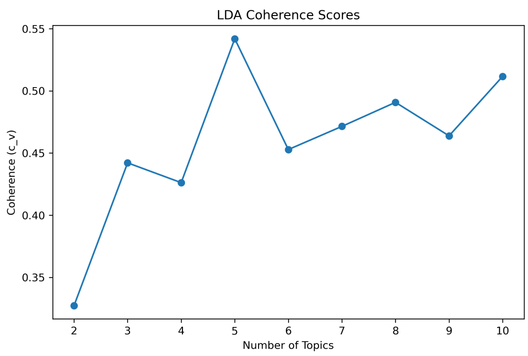


(d) Tweets from verified users

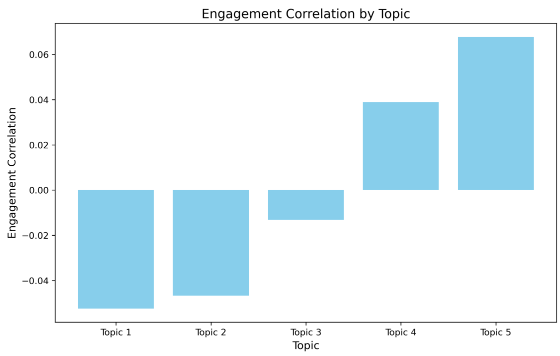
Figure 1: Comparison of average engagement for different tweet characteristics

full passes over the corpus were performed (passes=10). The hyperparameter alpha was set to 'auto' to allow automatic asymmetric prior estimation for document-topic distribution, improving the model's ability to capture topic sparsity. Additionally, `per_word_topics=True` enabled the extraction of topic distributions at the word level for more granular analysis. The top ten LDA model output keywords are displayed in Table 5 in the Appendix.

Subsequently, the topic contributions were correlated with engagement metrics using Pearson correlation to assess how topic prominence influenced user interaction. The resulting correlation measures a higher contributions from a topic associated with higher engagement (positive correlation) and a higher contributions from a topic associated with lower engagement (negative correlation). The correlation results between topics and engagement are displayed in Figure 2b.



(a) LDA coherence scores across models with 2 to 10 topics



(b) Engagement correlation by topic

Figure 2: Topic model evaluation and engagement correlations

Topic 1, with terms like 'agenda2030', 'climatescam', 'greatreset', and 'newworldorder', revolves around conspiratorial narratives linked to global agendas, environment, and health. This topic seems to frame climate action, global governance, and figures like Bill Gates as part of a coordinated elite conspiracy (i.e., 'their') to control populations under the guise of progress or sustainability. Topic 2, including keywords such as 'video', 'pfizer', 'información', focuses on suspicion towards mainstream narratives, especially pharmaceutical institutions (e.g., Pfizer), and could imply manipulation or concealment of information at the national (Spanish or Spanish-speaking regions) and international level. Topic 3 includes terms like 'plandemia' (a term combining 'plan' and 'pandemic' implying that the pandemic was orchestrated), 'world', 'wefpuppets', highlights the idea that global institutions (e.g., WEF) manipulate world events and public health crises ('plandemia'), positioning the globalist agenda as invasive. Topic 4 conveys resistance to perceived authoritarian impositions (e.g., 'sanitary dictatorships') and possibly loss of freedom under the new world order, potentially with regional references like Chile. It is also the topic more associated with Gardasil and HPV discussions. Finally, Topic 5 conflates public health (vaccines, COVID-19), geopolitical conflict (Ukraine/Russia), and political leadership (e.g., Giorgia Meloni) with a polarized moral framing ('malditaagenda2030'). The emergence of specific phrases such as Agenda2030, newworldorder, and wefpuppets reflects the blending of health discussions with political and social issues. This indicates the impact of concerns around these topics on the broader vaccine discussion.

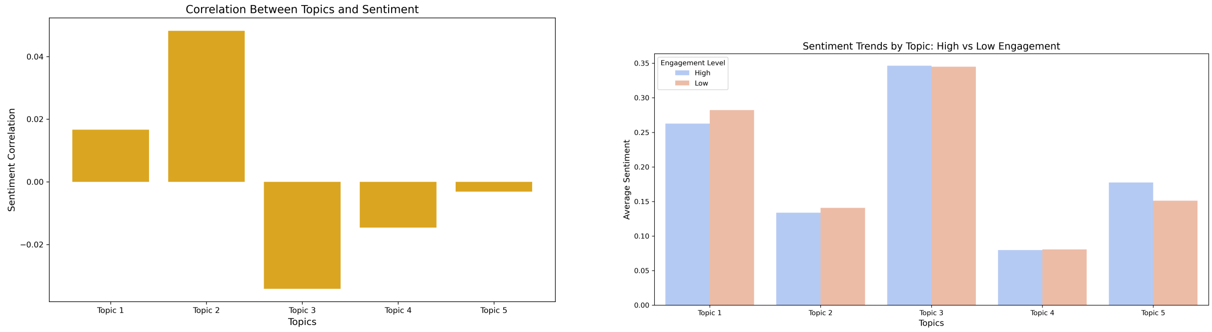
In terms of engagement, the Pearson correlation analysis indicates that Topic 4 and Topic 5 exhibit the highest positive correlation with engagement. Centred on conspiratorial and vaccine-related discussions, the result indicates significant public interest in pandemic-related conspiracies and globalist narratives. On the other hand, Topic 1, Topic 2, and Topic 3 show negative correlations with engagement. This result suggests that while topics such as climate conspiracies and WEF might be prevalent, they are less effective in driving audience interactions. This may suggest audience saturation towards these discussions or reduced credibility among mainstream users. In the next part, the analysis examines how sentiment within each topic impacts engagement to identify whether positive or negative tones drive interactions.

5.3. Sentiment analysis and topics' engagement

This part of the analysis examines the relationships between sentiment, topics, and engagement levels by exploring correlations, sentiment distribution, and average topic contributions for high- and low-engagement posts. This will offer insights about which topics drive more audience interaction in relation to sentiment. First, sentiment analysis (SA) was performed on the entire data-set using the XLM-RoBERTa multilingual sentiment model [69]. This model was chosen because it was trained specifically for Twitter sentiment analysis and supports over 50 languages, including those present in the data-set.

After performing SA, the Pearson correlation coefficient was calculated between the topic contribution (i.e., the degree to which a tweet associated with a specific topic drove engagement, as in previous step) and the sentiment text polarity (positive, neutral, or negative) (see 3a). A median engagement value was first used to categorize tweets into tweets with engagement above the median (i.e., high engagement) and tweets with engagement at or below the median (i.e., low engagement). Afterwards, mean sentiment values were calculated to examine whether high-engagement tweets are more positive or negative compared to low-engagement ones. Figure 3b shows the range and variance of sentiment in each group for each topic. Positive bars represent more positive sentiment overall (i.e., average sentiment > 0) whereas negative bars indicate more negative sentiment overall (i.e., average sentiment < 0). Colours are used to highlight differences between high (blue) and low (red) engagement, independent of the actual sentiment polarity.

The overall sentiment is positive across all topics. Topic 3 has the highest sentiment suggesting that discussions around conspiracies the health crisis and global institutions elicit more supportive reactions. Tweets here may be ironically enthusiastic or rallying support around anti-globalist claims, leading to a net positive tone. Topic 1 and Topic 2 display that more neutral or slightly negative tones (e.g., skepticism towards 'agenda2030' or climate issues) resonate more with the audience driving higher



(a) Overall sentiment correlation with engagement per topic

(b) Sentiment trends by topic of high vs low engagement

Figure 3: Pearson correlation between sentiment, topics and engagement

engagement. This suggests that engagement may be driven by controversial or critical discussions. Topic 4 exhibits the lowest average sentiment for both high- and low-engagement tweets. As this topic is one of the two that exhibit the highest engagement overall, this indicates that sentiment may not be a primary driver of engagement for it. In Topic 5, more positive sentiment correlates with higher engagement indicating that content on geopolitical events, health issues, and political figures may boost average positivity. This may suggest that audiences respond more to affirmative or supportive tones.

As the net sentiment remains above zero, the results point to an ironic usage of positive tones, for example mocking conspiracies, or supportive discourse towards them. Overall, topics referencing global agendas and conspiracies seem to be discussed in a supportive way which, especially in high-engagement tweets, may mean overall disinformation endorsement.

5.4. Language and engagement

This part of the analysis examines possible language-specific differences that can indicate that audience responses vary significantly according to cultural or linguistic factors. Conversely, if very weak or no correlation is found, this may indicate that other factors (e.g., topic relevance) might play a larger role in driving engagement. The data-set language classification was performed using Fasttext [70] which identified 30 languages. The language distribution across posts is provided in the Appendix. Given the uneven distribution of languages in the data-set—where Spanish, English, and French collectively account for approximately 49.4% of all tweets (see Table 1)—average engagement was calculated for the ten most represented languages to enhance the robustness and generalisability of the findings.

Language	Number of posts
ES	2035
EN	2000
FR	524
DE	136
NL	118
IT	85
PT	66
TR	55
CA	39
SV	24

Table 1: Ten most represented languages in the data-set

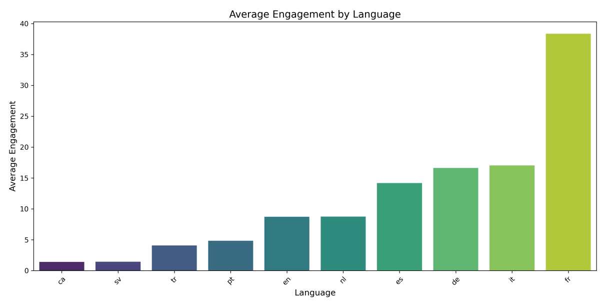
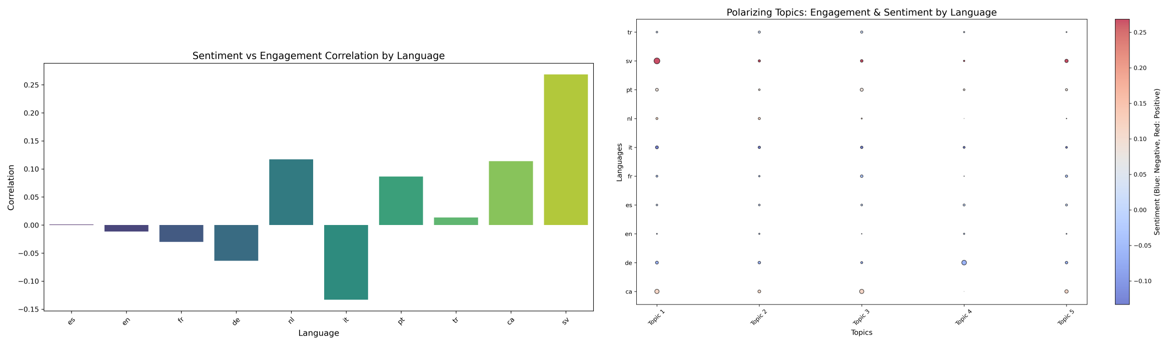


Figure 4: Engagement Correlation by Language

First, the correlation between language and engagement was calculated for these languages, with results shown in Figure 4. Although the overall correlation is weak (0.030), there are significant disparities between languages. French (fr) has the highest average engagement, indicating that tweets in French perform exceptionally well in terms of likes, replies, and retweets. In contrast, languages like Swedish (sv) and Catalan (ca) show the lowest engagement, while German (de) and Spanish (es) are in the middle. This may suggest limited content or lower user activity in these languages. The stark contrast between French and other languages underscores how audience responses vary, with the near-zero overall correlation indicating that language alone does not systematically drive engagement across the dataset, though individual languages may exhibit distinct patterns.

Next, the correlation between sentiment and engagement by language was calculated to examine cultural differences. The results, displayed in Figure 5a, show that Swedish (sv) has the highest positive correlation, meaning more positive sentiment aligns with higher engagement in Swedish tweets. Languages like Catalan (ca), Dutch (nl), and Spanish (es) also show positive correlations, while Italian (it), German (de), and French exhibit negative correlations, suggesting that negative sentiment may attract more engagement in these languages. This implies that more positive sentiment can reduce engagement, while negative sentiment may drive more attention. A few languages, such as English and Spanish, show minimal correlation, indicating that sentiment has little effect on engagement in these cases. This suggests that content topic might be a more significant factor in these languages. Overall, while sentiment can influence engagement, the effect appears language-specific and modest, highlighting the complexity of audience dynamics and the need for localized content strategies.



(a) Sentiment and engagement correlation by language.

(b) Polarising topics by language.

Figure 5: Correlation between sentiment, topics, and engagement by language.

The analysis examines the correlation between topics and engagement across different languages, aiming to identify variations and patterns in potentially polarizing and audience-dependent topics. Results are shown in Figure 5b, where each bubble represents the relationship between a language and a topic, with bubble size indicating the strength of the engagement correlation. Larger bubbles signify stronger correlations, while the colour indicates sentiment: blue for negative and red for positive, with darker shades representing stronger sentiment polarity.

The results indicate that engagement with all topics is generally associated with negative sentiment across most languages. However, some languages show different patterns: Swedish (sv) exhibits strong positive engagement, particularly with Topic 1 (large red bubble), suggesting users react positively to conspiratorial narratives about climate change and global agendas. Catalan (ca) shows moderate engagement with slightly positive sentiment for Topics 1 and 3, reflecting discussions on pandemic conspiracies. Italian (it) and German (de) show medium blue bubbles across all topics, indicating moderate engagement and negative sentiment, possibly reflecting skepticism towards health-related authoritarian narratives. Dutch (nl) displays low engagement and sentiment neutrality, with small bubbles and pale colors. English (en) has very small bubbles, suggesting weak engagement and sentiment polarity. Finally, French (fr), Turkish (tr), and Portuguese (pt) show moderate engagement, with smaller, neutral-to-lightly-colored bubbles.

Overall, the results reveal that reactions to disinformation topics are highly language-specific. For example, Topic 1 (likely related to broad conspiracies like Agenda 2030) is polarizing in Swedish and Italian but less so in English and Dutch. Topic 3 triggers negative sentiment in several European languages (it, de), while Topic 4 sees positive engagement in some communities like Swedish and Portuguese. Catalan and Swedish emerge as particularly responsive, with strong sentiment and engagement, indicating these communities are more engaged with disinformation. These findings highlight the importance of tailoring content strategies to match language-specific sentiment trends and audience's cultural identities.

6. Discussion

The findings of this study provide valuable insights into how cultural and linguistic factors shape user engagement with disinformation, especially in multilingual contexts. One key outcome is the clear evidence that disinformation engagement is not universal; it is influenced by linguistic and cultural nuances. For example, negative sentiment tweets in French, German, and Italian showed high engagement, suggesting that negative tones in these languages foster more interaction. In contrast, Swedish tweets displayed positive sentiment and engagement, revealing a culture-specific response to certain narratives. This highlights the need for a multicultural approach when examining disinformation-related user behaviour.

The topic modelling and sentiment analyses revealed several key trends. Topics on globalist agendas (e.g., Topics 1 and 3) and vaccine-related discussions (e.g., Topic 4) saw the highest engagement, particularly in Swedish and German, indicating strong public interest in health-related disinformation in these communities. Conversely, broader conspiracy topics like 'Agenda 2030' and 'The Great Reset' exhibited high engagement across various languages, suggesting widespread interest in these narratives. Language-specific trends in sentiment and engagement further highlight cultural and emotional influences. For example, Swedish and Catalan users responded positively to positive sentiment content, while German, Italian, and French users showed stronger engagement with skeptical or neutral sentiment. Furthermore, the study highlighted the role of verified user status and multimedia content in driving engagement. Tweets by verified users and those with multimedia elements consistently garnered higher interaction, emphasizing the importance of perceived credibility and visual content in amplifying disinformation.

This study provides critical insights for fostering healthier online discourse, empirically validating how language-specific sentiment, topic relevance, and engagement intersect in multilingual contexts. The identified language- and culture-specific patterns offer a foundation for designing targeted mitigation strategies which can be tailored to align with the emotional and cultural dynamics of different linguistic communities. Additionally, the study's findings on verified users and multimedia content suggest strategies for platform moderation. Platforms could leverage visual content and prioritize credible sources while limiting content from unverified accounts spreading disinformation.

7. Conclusions

This study shows how linguistic and cultural factors significantly shape disinformation engagement, challenging the idea of a universal audience response. Analysing over 5,000 tweets in 30 languages, the research reveals that disinformation's effectiveness varies across linguistic and cultural contexts, influenced by sentiment, topic relevance, and audience demographics. The findings therefore highlight the need for a multilingual and multicultural approach in disinformation mitigation. Tailoring strategies to the cultural and linguistic dynamics of different communities allows policymakers, researchers, and social media platforms to promote more informed and resilient public discourse, reducing the harmful impacts of disinformation. Finally, the emergence of COVID-19, climate change, and Agenda 2030-related topics suggests their influence on the broader vaccine discussion. This indicates that global issues are reshaping public discourse around vaccines; as discussions become more complex and interconnected, public health messaging must address a wide range of concerns, with comprehensive approaches being more effective than isolated messaging.

8. Limitations

Despite its comprehensive scope, this study has a number of limitations. First, the data-set has an uneven distribution of languages, with some languages being overrepresented and others having significantly fewer tweets. This discrepancy could bias the findings and limit generalizability. Future studies could address the languages uneven data-set distribution by actively sampling the under-represented languages.

Second, the reliance on engagement metrics such as likes, shares, and retweets may not reflect deeper cognitive or emotional responses. Future studies could incorporate qualitative methods, such as user interviews and linguistic analysis of the tweets, to gain deeper insights into cognitive and emotional responses. Finally, future works could investigate the role of platform algorithms in amplifying certain types of disinformation across different linguistic and cultural contexts, to expand the scope of the analysis and enhance our understanding of how to combat online disinformation.

Declaration on Generative AI

During the preparation of this work, the author used GPT-4o in order to: Grammar and spelling check and to generate images. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

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Feature	Statistic	p-value	DFs	Without Feature	With Feature
Multimedia Content	2.17	0.030	5181.0	12.94	18.92
Verified Users	9.95	4.09e-23	5181.0	10.92	50.64
Hashtags	-0.30	0.762	5181.0	18.00	14.10
Mentions	-0.65	0.515	5181.0	14.43	12.42

Table 2
Summary of T-Test Results and Engagement Statistics

Table 3
Data-set description

Attribute	Value
Number of likes	40,007
Number of comments	5,276
Number of shares	26,078
Number of users	2,668
Number of mentions	1,822
Number of verified users	419
Number of hashtags	17,293
Number of retweets	26,078
Number of quotes	1,866
Number of replies	5,276

Table 4
Top 20 most used hashtags

Hashtag	Count
#Agenda2030	3,421
#Gardasil	687
#agenda2030	388
#WEF	372
#GreatReset	178
#gardasil	161
#ClimateScam	154
#HPV	142
#NWO	137
#NewWorldOrder	116
#Agenda2030.	98
#AGENDA2030	95
#NOM	83
#Agenda21	72
#Plandemia	70
#nwo	70
#Agenda2030,	69
#KlausSchwab	68
#DigitalID	64
#ODS	62

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
0	agenda	video	plandemia	gardasil	covid19
1	climatescam	piped	world	chile	noalaagenda2030
2	greatreset	contra	mundo	merck	watch
3	todos	sobre	mundial	papillomavirus	ukraine
4	newworldorder	pfizer	wefpuppets	libertad	russia
5	agenda21	información	están	nuevoordenmundial	vacunas
6	billgates	nothing	repentinitis	wefpuppet	being
7	people	naciones	globalista	globalismo	giorgiameloni
8	their	humanidad	ahora	entre	malditaagenda2030
9	global	nicht	about	dictadurasanitaria	goodnews

Table 5
Top ten keywords associated with each Topic

Table 6
Language distribution in the data-set

Language Code	Count
es	2035
en	2000
fr	524
de	136
nl	118
it	85
pt	66
tr	55
ca	39
sv	24
pl	17
fi	17
fa	12
ja	11
war	8
ar	6
no	5
el	3
gl	3
id	3
la	2
hi	2
sl	2
zh	2
af	2
sr	1
ta	1
ru	1
mk	1
eu	1
uk	1