What drives engagement with disinformation on social media? A Social Identity Approach

Anonymous ACL submission

Abstract

This study investigates how linguistic and collective identity shape user engagement with disinformation online. It hypothesizes that sharing, commenting on, and reacting to disinformation operate as discursive practices that encode both collective agency and cultural-linguistic identity. Drawing on Social Identity Theory (SIT) and the Social Identity Model of Collective Action (SIMCA), the research analyzes a bilingual corpus of 4,085 tweets (2,000 in English and 2,035 in Spanish) collected via disinformation-related hashtags (e.g., #Agenda2030, #TheGreatReset) and enriched with credibility ratings from the Iffy+ list. Statistical, topic modelling, and cross-linguistic analyses of language choice and call-to-action expressions (e.g., mobilization phrases) reveal subtle contrasts: Spanish-speaking users engage more consistently with disinformation but not significantly more with mobilizing language, while English-speaking users display less predictable interaction patterns. These findings refine the application of SIT and SIMCA to disinformation engagement, suggesting that the mere presence of mobilizing language is insufficient to spur measurable interaction. The results highlight the importance of accounting for linguistic and cultural variation—such as emotional valence and narrative framing—in both disinformation research and the design of targeted mitigation strategies.

1 Introduction

Online disinformation—understood here as the deliberate dissemination of false or misleading content with the potential to cause public harm (Tucker et al., 2018)—has surged in recent years, particularly in the wake of the COVID-19 crisis. Widely acknowledged as a major threat to public and individual safety, substantial research has examined its structure (Van Prooijen and Douglas, 2018; Van Prooijen and Van Vugt, 2018), spread (Bonnevie et al., 2021), impact (Simms et al., 2020; Stabile et al., 2019; Chen et al., 2020), and content (Wiggins, 2023; Demata et al., 2022; Fallis, 2009). Scholars have also investigated the role of conspiracy theories and disinformation in shaping public perceptions and decision-making (Chen et al., 2021; Yagi et al., 2024), as well as the influence of network structures and user interactions in amplifying disinformation (Quintana et al., 2022; Gunaratne et al., 2019). More recently, attention has turned to understanding the deeper mechanisms through which disinformation persuades individuals to accept unlikely or false narratives, giving more importance to the cognitive and identity-based factors that may explain why individuals engage with disinformation (Reddi et al., 2023; Bastick, 2021; Butter and Knight, 2020).

Despite the rapid growth of this field, however, the fundamental reasons behind user engagement with disinformation remain poorly understood. Some researchers argue that this gap stems from contradictory and fragmented findings (Birchall and Knight, 2022; Kirchner and Reuter, 2020), while others point to the overly functionalist approach to disinformation, treating it as merely 'the opposite of true' and overlooking its cognitive and subjective dimensions (Viola, 2025b; Reddi et al., 2023; Bastick, 2021). This often leads to disinformation consumers being dismissed as irrational or paranoid actors and to counter-measures being mostly inefficient (Alava et al., 2017; Conway, 2017; Johnson, 2018; Mølmen and Ravndal, 2021; Reicher and Haslam, 2016).

This study contends that a critical gap in the literature lies in the failure to address the role of linguistic and cultural identity in driving engagement with disinformation. It argues that engagement with disinformation is not merely an act of passive belief but an active discursive process, where individuals construct and negotiate their cultural identities. It further argues that interacting with disinformation—through shares, comments, reactions,

and reposts—constitutes a discursive practice that equally encodes collective agency. This behaviour would be shaped by perceived injustice, disillusionment with mainstream media, and the affordances of alternative information ecosystems (Wintterlin et al., 2023).

These arguments are supported by two key considerations. First, much of the current research on disinformation remains disproportionately focused on a small subset of industrialized democracies, particularly the United States and the United Kingdom (Bajaj, 2024). A study by Seo & Faris (Seo and Faris, 2021) found that 62.8% of empirical studies published in communication journals between 2015 and 2020 relied on U.S.-based data (p. 1166). Scholars such as Bajaj (Bajaj, 2024) highlight that disinformation is not a universal phenomenon and that this geographical bias distorts our understanding of its cultural dimensions. Consequently, mitigation efforts that ignore these cultural dynamics risk being ineffective.

Second, disinformation has been linked to citizens' decrease of trust in mainstream media and other sources of authoritative information (MacFarquhar, 2016; Lewis and Marwick, 2017; Allcott and Gentzkow, 2017), mistrust of establishment political figures and institutions and increased acceptance of – or indeed support for – fringe, anti-establishment or radical actors and movements (Beauchamp, 2019; Amlinger, 2022; Reichardt, 2022). Research on the 2020 health crisis, for example, has demonstrated that COVID-19 disinformation motivated individuals to protest by offering a sense of agency and empowerment (Reichardt, 2022; Amlinger, 2022; Birchall and Knight, 2022). Thus, according to this view, even unlikely or improbable disinformation narratives succeed in mobilizing individuals by fostering a belief in their capacity to effect change. In this sense, online participation—expressing dissent, signing petitions, or sharing content—would function as a low-cost form of collective action (Brunsting and Postmes, 2002). Through social media, users can signal group membership, express opposition to elites, and reinforce a shared identity, transforming engagement with disinformation into a performative act of resistance. Online activities such as sharing or liking content offers an easy and effective way for people to express dissent with others or to demonstrate their belonging to a group. Following on these considerations, this study conceptualizes engagement with disinformation as a form of online collective action, driven by cultural and linguistic group identity and opposition to elite narratives.

Further, this study advocates for a broader, comparative, and multilingual approach in disinformation research that investigates linguistic and cultural identity-based differential experiences of disinformation. To this aim, the paper analyses 4,085 disinformation tweets in English (EN) and Spanish (ES). Using statistics, topic modelling, and linguistic analysis, the study examines how linguistic features, topical themes, and call-to-action expressions shape user engagement, using metrics such as likes, retweets, quotes, shares, and replies. The results emphasize the influence of linguistic and cultural identity factors in shaping individuals' susceptibility to persuasive disinformation narratives. They also offer a nuanced perspective that examines the shared symbols and thematic patterns that resonate with social media users in complex environments, such as the Internet.

2 User engagement, disinformation, and collective action

The scholarly literature on user engagement in online and social media contexts has approached this phenomenon through various conceptual frameworks and methodologies. Engagement is often conceptualized as user-initiated actions that contribute to value co-creation, as proposed by Brodie et al. (Brodie et al., 2013). This broad definition underscores the interplay between behavioural, cognitive, and emotional dimensions of engagement, emphasizing the need to explore its motivations and nuances. Shao (Shao, 2009) categorized user interaction into three primary behaviours: consumption (viewing and reading), participation (interacting with content), and production (creating and uploading content). Following this framework, researchers have examined how engagement manifests across platforms, particularly differentiating between active participation and passive consumption. On Facebook and YouTube, active engagement involves actions such as liking, commenting, and sharing, whereas passive engagement consists of clicking, watching, or hovering over content (Kaur et al., 2019; Khan, 2017). On X (formerly Twitter), active engagement further includes retweeting, quoting, and following (Chen, 2011). Studies also highlight the prevalence of passive users (often called 'lurkers'), who primarily consume content without actively engaging, com-

prising up to 90% of users in many online communities (Nonnecke and Preece, 1999; Preece et al., 2004). This contrast between active contributors and passive consumers underscores the need to understand what motivates users to actively engage with content, particularly disinformation.

Recent research has therefore explored the drivers of engagement with disinformation and fake news on social media. Emotionally charged content has been identified as one of the strongest amplifiers of engagement, with sensationalized headlines and narratives strategically crafted to trigger emotional responses such as fear, anger, and anticipation, thus encouraging interaction and dissemination (Horner et al., 2023). Additionally, visual elements seem to play a significant role in enhancing credibility and audience response (Cao et al., 2020; Viola, 2025a). Features such as clickbait, emotionally charged language, and references to specific individuals, organizations, or events further heighten emotional resonance, thereby boosting engagement (Ali et al., 2023). Other factors influencing the likelihood of sharing disinformation would include fear of missing out, source credibility, information quality, cognitive overload, and social media fatigue (Kumar et al., 2020; Islam et al., 2020). These content strategies capitalize on psychological triggers to grab attention, manipulate perceptions, and enhance virality.

Furthermore, the role of content creators in the spread of disinformation seems to be critical (Vilella et al., 2022). Audiences would be more likely to trust and engage with content from sources they perceive as authoritative and credible (Dennis et al., 2023). This would explain why disinformation spreaders often exploit trust by mimicking legitimate sources or leveraging the reputations of influential figures (Housholder and LaMarre, 2014). Conversely, established content creators with verified accounts and large followings benefit from increased credibility, making their content more likely to be accepted and widely shared (Dubois et al., 2020). Research has indeed shown that emotionally provocative disinformation—particularly fear-inducing, anger-driven, or surprising content—spreads more rapidly when disseminated by trusted users with significant audiences (Fan and Lederman, 2018).

This study builds upon these findings and integrates the Social Identity Theory (SIT) (Tajfel and Turner, 2004) with the Social Identity Model of Collective Action (SIMCA) (Tajfel and Turner, 2004; Turner, 1991; van Zomeren et al., 2008) to provide a theoretical lens for understanding engagement with disinformation. The SIT framework claims that users engage with content that reinforces their group identity (e.g., linguistic communities, national identity, ideological affiliations). According to this view, engagement is driven by in-group/out-group dynamics, where users support content aligned with their identity and oppose conflicting narratives. In this study, in-group is operationalised as linguistic and cultural identity (i.e., English speaking communities and Spanish speaking communities). Given the absence of specific multilingual and multicultural frameworks for user engagement, SIT provides valuable insights into why users are more likely to engage with content that reflects their linguistic and cultural identity, reinforcing their sense of group belonging in online spaces.

The SIMCA framework posits that collective action is driven by three interrelated psychological mechanisms: social identity, perceived injustice, and anger combined with participatory efficacy. Applied to disinformation, this model helps explain why users engage with misleading narratives not just as passive consumers but as active participants in a form of digital collective action. According to SIMCA, group identification fosters a sense of belonging, reinforcing shared beliefs and in-group solidarity. Hence, individuals who engage with and disseminate disinformation often align themselves with a social group opposed to mainstream narratives (Wintterlin et al., 2023).

Many disinformation narratives frame mainstream institutions (e.g., governments, media, academia) as corrupt or oppressive, fuelling distrust and resentment (Reichardt, 2022). SIMCA suggests that perceived injustice strengthens motivation for collective action, which in the digital sphere translates into engaging with and sharing disinformation as an act of defiance. Finally, emotionally charged content—particularly anger-driven messages—has been shown to increase disinformation engagement (Horner et al., 2023). According to SIMCA, anger acts as a mobilizing force, prompting individuals to take action, while participatory efficacy (the belief that engagement can effect change) encourages users to share disinformation as a means of collective resistance.

By situating disinformation engagement within the SIT and SIMCA frameworks, this study argues that language and culture shape how users interpret

and interact with misleading narratives. Emotions such as fear, anger, frustration, and distrust are deeply influenced by cultural values, lived experiences, and social identities (Viola, 2025b). While social media may amply these emotional responses (Bonnevie et al., 2021; Puri et al., 2020), reducing the phenomenon of disinformation to a mere consequence of digital platforms would be an oversimplification (Nguyen and Catalan-Matamoros, 2022). Engagement with disinformation is on the contrary a complex socio-cognitive process, driven by individual traits (e.g., cultural background, personal beliefs, and values) (Buturoiu et al., 2021; Hornsey et al., 2023), intergroup identity dynamics (Cookson et al., 2021; Turner, 1991), and broader sociopolitical conditions such as populism (Demata et al., 2022) and declining trust in institutions (Nguyen and Catalan-Matamoros, 2020).

To investigate these dynamics, this study examines the relationship between language, identity, and call to action expressions in shaping engagement with disinformation. The findings contribute to a data-driven understanding of how disinformation operates as a tool of collective agency, offering insights into the role of shared discourse in reinforcing identity and mobilizing online action.

3 Data and methodology

Data retrieval was conducted through targeted queries that extracted tweets containing specific hashtags, including *#Agenda2030*, *#The GreatReset*, *#NewWorldOrder*, *#wefpuppets*. These hashtags have been found in the literature as typically associated with disinformation, fake news, and conspiracy theories (Laquièze, 2025; Christensen and Au, 2023; Sa'ad Abdullahi and Pindiga, 2023). The full list of the seed hashtags is provided in the Appendix. Additionally, the data-set was enriched with information about content diffusion and filtered for tweets drawn from sources known for low credibility, as identified in the Iffy+ list (Golding, 2025), which catalogues 2,042 outlets flagged by professional fact-checkers as non-reliable sources —a method commonly employed in prior work (DeVerna et al., 2024; Yang et al., 2021)[1]. The data-set was later pseudomysed to remove any identifiable references and it can be provided upon request to the author[2].

The working data-set covers a total duration of 394 days spanning a time period from 1 August 2022 to 30 August 2023. It contains 4,035 tweets in two languages almost identically distributed (2,000 in English - EN, 2,035 in Spanish -ES) thus making the two sets highly comparable. The data-set also includes several attributes such as the tweet texts, the hashtags, likes, replies, retweets, shares, and quotes count. A detailed description of the data-set is given in Table 7 in 8.

This study posits that analyzing user engagement with the selected posts provides quantifiable insights into the relationship between language, identity, and collective agency and the dissemination and reception of disinformation. Here, engagement is operationalized as the cumulative sum of likes, shares, retweets, quotes, and replies associated with each tweet, as found in the literature (Chen, 2011). Collective agency is operationalised through the use of mobilising language, for instance explicit call-to-action expressions (e.g., 'Resist the reset', 'donotcomply') but also power-laden language (e.g., us vs. them frames, agency attribution) and thematic organisation (e.g., New World Order, WEF Puppets). First, Embedding-Based Topic Modelling using BERTopic (Grootendorst, 2022) is applied to the corpus to identify key themes in the data-set. From the topics obtained, the author performed a qualitative analysis on the most representative tweet per topic so as to identify mobilising language (*cfr.* 4.3). Additionally, further expressions were extracted applying Critical Discourse Analysis (CDA) (Dijk, 1985, 1997) on a sample of 200 tweets (100 tweets per language).

4 Analysis

4.1 Statistical analysis of language and engagement

The analysis first examines possible language-specific differences that can indicate that audience responses vary significantly according to linguistic factors. Conversely, if weak or no correlation is found, this may indicate that other factors (e.g., superspreaders, bots, collective action) might play a larger role in driving engagement. The results are displayed in Table 1.

Given that English tweets were encoded as 1 and Spanish tweets as 0, the negative Pearson correla-

[1]The author acknowledges that while this strategy allows for broad coverage, it cannot account for the fact that not all the posts in the data-set contain links to external content and that individual articles from a low-credibility outlet may still be accurate.

[2]The data-set will be publicly released following ethical approval.

Test	Statistic	p-value	Interpretation
Pearson correlation (language–engagement)	$r = -0.0422$	$p = 0.0074$	Weak but significant negative correlation; Spanish-language tweets receive slightly higher engagement.
Kruskal–Wallis test (language–engagement)	$H = 21.808$	$p = 3.01 \times 10^{-6}$	Significant difference in engagement distributions across languages.
Pairwise comparison (EN vs. ES)	$U = 1{,}869{,}946$	$p < 10^{-5}$	English and Spanish differ significantly; Spanish tweets show higher engagement levels.

Table 1: Summary of statistical tests examining the relationship between language and engagement metrics.

tion coefficient ($r = -0.0422, p = 0.0074$) indicates that engagement decreases slightly as the language variable increases from Spanish to English. In other words, Spanish-language tweets tend to receive higher levels of engagement than English-language ones. This finding is further supported by the Kruskal–Wallis test ($H = 21.808, p = 3.01 \times 10^{-6}$), which reveals significant differences in engagement across languages, and by the pairwise Mann–Whitney comparison ($U = 1{,}869{,}946, p < 10^{-5}$) confirming that the disparity between English and Spanish engagement is statistically significant. Although the effect size is small, the consistency across tests suggests a robust linguistic pattern, where Spanish tweets elicit comparatively stronger audience interaction. This difference may reflect broader variations in audience composition, regional discourse dynamics, or the communicative framing characteristic of Spanish-speaking communities.

The next section examines the presence of superspreaders and investigates the effect on engagement levels.

4.2 Superspreaders and Bot activity

We now examine whether the presence of superspreaders in the data-set shifts the language and/or the engagement balance. First, superspreaders were identified using a multi-dimensional engagement and network-activity criterion, operationalized according to three criteria: per-user engagement metrics, conversational out-degree, and thresholding (DeVerna et al., 2024). Per-user engagement was calculated by computing three summary statistics on retweet volume and three on reply volume for each user in the data-set as explained below:

- **Retweet sum** ($\mathrm{rt_sum}_i$): the total number of times user i's tweets were retweeted.
- **Retweet mean** ($\mathrm{rt_mean}_i$): the average number of retweets per tweet for user i.
- **Retweet max** ($\mathrm{rt_max}_i$): the highest retweet count received by any single tweet of user i.
- **Reply sum** ($\mathrm{rp_sum}_i$): the total number of replies received by user i's tweets.
- **Reply mean** ($\mathrm{rp_mean}_i$): the average number of replies per tweet for user i.
- **Reply max** ($\mathrm{rp_max}_i$): the maximum number of replies received by any single tweet of user i.

These six metrics captured both total volume (sum), typical activity level (mean), and individual peaks (max).

Conversational out-degree was then computed to assess how broadly each user initiated or contributed to discussions. This was operationalized by constructing a directed reply network in which each edge represented a reply from one user to another. A user's out-degree thus indicated the number of distinct users they replied to. Finally, the top five percent of users on each metric were identified independently to define the superspreader threshold. A user was designated a superspreader if they ranked in the top 5 percentile on any of the five measures (aggregate retweets, peak retweets, aggregate replies, peak replies, or out-degree). This approach ensured that both consistently active amplifiers and users responsible for individual cascades could be captured. The results stratified by the language of the user's tweets are displayed in Table 2 below.

The results present descriptive statistics for each superspreader metric, stratified by the language of the user's tweets (English EN vs. Spanish ES). Most notable insights include that among the identified superspreaders, English users (N = 248) tend to reply to more distinct users (median out-degree = 3) than Spanish users (median = 1). Spanish superspreaders receive slightly more replies on average (mean rp-sum = 7.57 vs. 6.73) and exhibit higher reply peaks (mean rp-x = 5.50 vs. 4.17). Retweet behaviour is comparable across languages: mean retweet peak (20) and sum (44 EN vs. 36 ES) show only modest differences. Based on the metrics, a total number of 1,915 superspreaders was identified

Language	Statistic	out-degree	rp-max	rp-sum	rt-max	rt-sum
EN	50%	3.00	1.00	2.00	2.00	3.00
	75%	5.00	2.00	3.00	10.00	15.25
	Total	248.00	248.00	248.00	248.00	248.00
	Max	45.00	131.00	219.00	808.00	2495.00
	Mean	4.25	4.17	6.73	20.61	44.07
	Min	0.00	0.00	0.00	0.00	0.00
	Std	7.00	13.16	22.98	80.74	216.37
ES	50%	1.00	1.00	2.00	2.50	4.00
	75%	4.00	2.00	3.00	10.00	13.75
	Total	286.00	286.00	286.00	286.00	286.00
	Max	48.00	354.00	440.00	808.00	2495.00
	Mean	3.20	5.50	7.57	19.75	35.78
	Min	0.00	0.00	0.00	0.00	0.00
	Std	5.42	25.39	33.42	75.23	191.84

Table 2: Summary statistics (50th %, 75th %, total count, maximum, mean, minimum, and standard deviation) of superspreader metrics by language (EN vs. ES).

(940 for English and 975 for Spanish). This means that in English, superspreaders account for about 43% of tweets, with the remaining 57% by others whereas in Spanish, superspreaders contribute around 48%, with 52% by other users (Figure 1).

Given the high number of superspreaders, the identified tweets and accounts were removed from the data-set; the remaining accounts were further inspected for potential bots using *BotometerLite* (Observatory on Social Media). *BotometerLite* produces scores derived from historical Twitter data collected prior to 31 May 2023, thereby aligning with the data-set's temporal scope and estimating the likelihood that a user was a bot at the time of observation. As none of the accounts was scored as a potential bot, no further filtering was applied to the data-set which finally included 1,140 tweets in English and 1,060 in Spanish, making the two sets once again highly comparable.

After excluding superspreaders from the data-set, the correlation between language and engagement remained negative and statistically significant (Table 3). The slightly stronger effect size compared to the full data-set ($r = -0.0422$) indicates that the association is not driven by highly influential accounts. Instead, it reflects a consistent pattern across ordinary users, where Spanish-language tweets continue to receive higher engagement than English-language ones. This suggests that the language effect is robust and likely rooted in broader audience dynamics rather than the disproportionate impact of superspreading actors. In the next section, the analysis investigates if such differences can be attributed to the effect of collective action

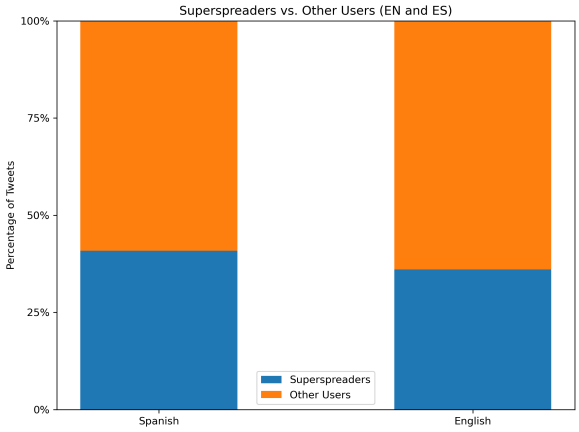

Figure 1: Superspreaders vs other users in English and Spanish

expressions in driving engagement with disinformation.

Pearson r	p-value
-0.0762	0.0003

Table 3: Pearson Correlation Test Results between language and engagement without superspreaders

4.3 Collective action

This part of the analysis now investigates the role of collective action language in user engagement with disinformation tweets. The research hypothesis is that perceived injustice strengthens motivation for collective action, which in an online environment would translate into engaging with and sharing disinformation as an act of defiance and regained agency. The methodology follows a lin-

guistic and statistical approach: collective action language was defined as manifested in phrases that mobilise users towards participation or resistance as explained in 3.

4.3.1 Topic modelling

Topic modelling was used to identify tweets containing mobilising language and call-to-action expressions. Specifically, we used BERTopic with a multilingual SentenceTransformer (Grootendorst, 2022) as in the literature, it is found to outperform traditional LDA models on multilingual, short texts. Feature extraction was performed by applying a bag-of-words with unigrams and bigrams, and `max_df` $= 0.85$ and `min_df` $= 0.02$ to remove overly common/rare terms. The number of topics was fixed at ten to balance interpretability and thematic coverage. Preliminary runs with unconstrained topic discovery produced a larger number of fine-grained clusters, many of which overlapped semantically. Setting `nr_topics=10` allowed for a more coherent, high-level representation of discourse themes while retaining sufficient diversity to capture major narrative patterns across languages. This choice also ensured comparability across analyses and facilitated qualitative interpretation. The model returned per-document topic probabilities, per-topic term rankings, and most representative document per topic, enabling both quantitative summaries and qualitative interpretation across languages.

Several topics identified by the model displayed strong mobilising language, encouraging resistance, participation, or direct action against perceived threats linked to Agenda2030 and related governance narratives. Representative tweets (Table 4) show imperatives such as *"wake up," "stand up," "join,"* and *"resist,"* reflecting how conspiracy-linked discourses often blend moral urgency with collective calls to action. These patterns suggest that the discourse functions not only to inform or persuade, but to mobilise communities around shared narratives of opposition and control. The complete results are reported in Table 10 in 8.

Additionally, further expressions were extracted applying Critical Discourse Analysis (CDA) (Dijk, 1985, 1997) on a sample of 200 tweets (100 tweets per language). The full list of expressions (91 in English and 82 in Spanish) is provided in 8. Finally, language-specific engagement trends were analysed. The results are reported in Table 5.

With an r = 0.0027, there is virtually no linear relationship between whether an English tweet contains a call-to-action expression and its engagement. As the p-value is also large, the null hypothesis of no association cannot be rejected. In Spanish, a small positive r is found; this suggests a very weak tendency for CTA-containing Spanish tweets to have slightly higher engagement, but this effect is not statistically significant at the 0.05 level (p = 0.145). It can be concluded that there is no meaningful evidence call-to-action expressions significantly affect engagement—neither for English nor for Spanish.

Finally, a comparison with the data-set including superspreaders was conducted to examine if including superspreaders in the engagement calculations introduces bias or inflates CTA effects. The results are reported in Table 6 and show that including high-reach superspreader accounts does not materially alter the engagement levels. In both languages, the correlation between having a CTA and engagement remains essentially zero and non-significant meaning that superspreader activity does not drive a CTA–engagement relationship. This consistency strengthens confidence that CTA phrases, even when amplified by high-reach accounts, are not a reliable lever for boosting tweet engagement in the sample.

Topic ID	Key Terms	Representative Tweet (excerpt)
0	agenda2030, nwo, freedom, truth, resist, wakeup	"Wake up! Agenda2030 is control, not sustainability. Stand up and resist before it's too late."
8	digitalid, cbdc, surveillance, control, freedom	"Say no to digital IDs and CBDCs. Defend your privacy and take action now!"
3	canada, protest, trudeau, rights, people, unite	"Canadians must stand together for freedom. Join the protest and make your voice heard!"

Table 4: Representative topics and example tweets illustrating mobilising and resistance-oriented language.

Table 5: Correlation between CTA presence and engagement by language

Language	Pearson r	Point–Biserial r	p-value
English	0.0027	0.0027	0.927
Spanish	0.0447	0.0447	0.145

Table 6: Correlation between CTA presence and engagement by language with superspreaders

Language	Pearson r	Point–Biserial r	p-value
English	0.0021	0.0021	0.925
Spanish	0.0106	0.0106	0.634

5 Discussion

The statistic and cross-linguistic analysis yielded interesting insights into users' engagement with disinformation. It showed that language alone does not influence engagement with disinformation. Although Spanish tweets consistently received more engagement than English tweets, due to the very small -albeit statistically significant - difference, the correlation remains weak even after filtering out highly influential acconts, i.e., superspreaders.

The main analysis then examined whether the presence of explicit call-to-action (CTA) language influenced engagement. The results showed that although explicit CTA language is frequently found in disinformation and conspiratorial tweets, the CTA language at best excerts a negligible effect on tweet engagement in both English and Spanish tweets.

Interestingly, while Spanish tweets with CTA expressions showed a small positive r, this trend failed to reach significance. This suggests that, although directive language may resonate more within Spanish-speaking communities—as theorized by the Social Identity and Collective Action models—it does not reliably translate into higher engagement metrics on this platform. Conversely, English tweets exhibit virtually zero correlation, challenging the assumption that mobilization rhetoric is a universal engagement booster.

Further, including superspreader accounts in the analysis marginally attenuates the already negligible correlations, confirming that high-reach users do not drive a CTA–engagement relationship. Together, these findings suggest that CTA phrases—even when amplified by prominent accounts—are not an effective lever for increasing user interaction with disinformation content.

From a theoretical standpoint, these results nuance the application of Social Identity Theory (SIT) and the Social Identity Model of Collective Action (SIMCA) to disinformation engagement. While SIT/SIMCA correctly foreground the role of in-group identity and perceived injustice in motivating collective action, the mere presence of mobilizing language appears insufficient to spur measurable engagement behaviours on X. It may be that other linguistic features (e.g., emotional valence, narrative framing) or network-structural factors (e.g., algorithmic amplification) play a more decisive role in driving user interaction.

6 Conclusion

This study examined the relationship between language and collective action expressions in driving engagement with disinformation across English (EN) and Spanish (ES) tweets. By leveraging statistical and cross-linguistic analysis, the findings provide empirical evidence that language plays a moderate role, as Spanish tweets received the highest overall engagement, but language alone is not a strong predictor for engagement with disinformation.

Contrary to expectations, collective action expressions (e.g., mobilization phrases) had limited influence on engagement. While Spanish tweets with call-to-action expressions saw increased engagement, English did not exhibit similar trends. This suggests that mobilization language may resonate more strongly within certain cultural contexts but is not a universal driver of engagement. Overall, mobilization rhetoric appears to have limited utility as a tactic for boosting engagement with disinformation on X, underscoring the necessity of tailored strategies to understand and counteract disinformation spread.

7 Limitations

While this study provides valuable insights, several limitations must be acknowledged. The data-set consists of tweets from X, which may not be representative of broader social media engagement patterns on Facebook, YouTube, or TikTok. Future studies could investigate how different platforms' algorithmic amplification patterns alter engagement dynamics. Due to lack of resources, the study primarily analysed explicit collective action expressions from a sample of the data-set but did not account for *all* the mobilization strategies in the data-set. Further research should incorporate larger semantic and qualitative analysis to assess a larger range of such linguistic strategies.

Declaration on Generative AI

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

References

Séraphin Alava, Divina Frau-Meigs, Ghayda Hassan, Hasna Hussein, and Yuanyuan Wei. 2017. *Youth and violent extremism on social media: violent extremism on social media: mapping the research*. United Nations Educational, Scientific, and Cultural Organization, Paris. OCLC: 1089113298.

Maged Ali, Lucas Moreira Gomes, Nahed Azab, João Gabriel de Moraes Souza, M. Karim Sorour, and Herbert Kimura. 2023. Panic buying and fake news in urban vs. rural England: A case study of twitter during COVID-19. *Technological Forecasting and Social Change*, 193:122598.

Hunt Allcott and Matthew Gentzkow. 2017. Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, 31(2):211–236.

Carolin Amlinger. 2022. *Gekränkte Freiheit: Aspekte des libertären Autoritarismus*, erste auflage, originalausgabe edition. Suhrkamp, Berlin.

Shelly Ghai Bajaj. 2024. Digital Disinformation Threats and Ethnocultural Diasporas. In Gitanjali Adlakha-Hutcheon and Candyce Kelshall, editors, *(In)Security: Identifying the Invisible Disruptors of Security*, pages 53–65. Springer Nature Switzerland, Cham.

Zach Bastick. 2021. Would you notice if fake news changed your behavior? An experiment on the unconscious effects of disinformation. *Computers in Human Behavior*, 116:106633.

Zack Beauchamp. 2019. Social media is rotting democracy from within. *Vox*.

Clare Birchall and Peter Knight. 2022. *Conspiracy Theories in the Time of Covid-19*, 1 edition. Routledge, London.

Erika Bonnevie, Allison Gallegos-Jeffrey, Jaclyn Goldbarg, Brian Byrd, and Joseph Smyser. 2021. Quantifying the rise of vaccine opposition on Twitter during the COVID-19 pandemic. *Journal of communication in healthcare*, 14(1):12–19. ISBN: 1753-8068 Publisher: Taylor & Francis.

Roderick J. Brodie, Ana Ilic, Biljana Juric, and Linda Hollebeek. 2013. Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research*, 66(1):105–114.

Suzanne Brunsting and Tom Postmes. 2002. Social Movement Participation in the Digital Age: Predicting Offline and Online Collective Action. *Small Group Research*, 33(5):525–554. Publisher: SAGE Publications Inc.

Michael Butter and Peter Knight, editors. 2020. *Routledge handbook of conspiracy theories*. Routledge, Abingdon, Oxon ; New York, NY.

Raluca Buturoiu, Georgiana Udrea, Denisa-Adriana Oprea, and Nicoleta Corbu. 2021. Who Believes in Conspiracy Theories about the COVID-19 Pandemic in Romania? An Analysis of Conspiracy Theories Believers' Profiles. *Societies*, 11(4):138. Number: 4 Publisher: Multidisciplinary Digital Publishing Institute.

Juan Cao, Peng Qi, Qiang Sheng, Tianyun Yang, Junbo Guo, and Jintao Li. 2020. Exploring the Role of Visual Content in Fake News Detection. In Kai Shu, Suhang Wang, Dongwon Lee, and Huan Liu, editors, *Disinformation, Misinformation, and Fake News in Social Media: Emerging Research Challenges and Opportunities*, pages 141–161. Springer International Publishing, Cham.

Gina Masullo Chen. 2011. Tweet this: A uses and gratifications perspective on how active Twitter use gratifies a need to connect with others. *Computers in Human Behavior*, 27(2):755–762.

Li Chen, Qi Ling, Tingjia Cao, and Ke Han. 2020. Mislabeled, fragmented, and conspiracy-driven: a content analysis of the social media discourse about the HPV vaccine in China. *Asian Journal of Communication*, 30(6):450–469.

Li Chen, Yafei Zhang, Rachel Young, Xianwei Wu, and Ge Zhu. 2021. Effects of Vaccine-Related Conspiracy Theories on Chinese Young Adults' Perceptions of the HPV Vaccine: An Experimental Study. *Health Communication*, 36(11):1343–1353.

Michael Christensen and Ashli Au. 2023. The great reset and the cultural boundaries of conspiracy theory. *International Journal of Communication*, 17:19–19.

Maura Conway. 2017. Determining the Role of the Internet in Violent Extremism and Terrorism: Six Suggestions for Progressing Research. *Studies in Conflict & Terrorism*, 40(1):77–98. Publisher: Routledge _eprint: https://doi.org/10.1080/1057610X.2016.1157408.

Darel Cookson, Daniel Jolley, Robert C. Dempsey, and Rachel Povey. 2021. "If they believe, then so shall I": Perceived beliefs of the in-group predict conspiracy theory belief. *Group Processes & Intergroup Relations*, 24(5):759–782.

Massimiliano Demata, Virginia Zorzi, and Angela Zottola, editors. 2022. *Conspiracy theory discourses*. Number volume 98 in Discourse approaches to politics, society and culture. John Benjamins Publishing Company, Amsterdam ; Philadelphia.

Alan R. Dennis, Patricia L. Moravec, and Antino Kim. 2023. Search & Verify: Misinformation and source evaluations in Internet search results. *Decision Support Systems*, 171:113976.

Matthew R. DeVerna, Rachith Aiyappa, Diogo Pacheco, John Bryden, and Filippo Menczer. 2024. Identifying and characterizing superspreaders of low-credibility content on Twitter. *PLOS ONE*, 19(5):e0302201.

Teun A. van Dijk, editor. 1985. *Discourse and Communication: New Approaches to the Analysis of Mass Media Discourse and Communication*. DE GRUYTER.

Teun Adrianus van Dijk. 1997. *Discourse studies: a multidisciplinary introduction. 2, 2,*. Sage. OCLC: 634170329.

Elizabeth Dubois, Sara Minaeian, Ariane Paquet-Labelle, and Simon Beaudry. 2020. Who to Trust on Social Media: How Opinion Leaders and Seekers Avoid Disinformation and Echo Chambers. *Social Media + Society*, 6(2):2056305120913993.

Don Fallis. 2009. A Conceptual Analysis of Disinformation.

Hanmei Fan and Reeva Lederman. 2018. Online health communities: how do community members build the trust required to adopt information and form close relationships? *European Journal of Information Systems*, 27(1):62–89. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/0960085X.2017.1390187.

Barrett Golding. 2025. Iffy Index of Unreliable Sources.

Maarten Grootendorst. 2022. BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794*.

Keith Gunaratne, Eric A. Coomes, and Hourmazd Haghbayan. 2019. Temporal trends in anti-vaccine discourse on Twitter. *Vaccine*, 37(35):4867–4871.

Christy Galletta Horner, Dennis Galletta, Jennifer Crawford, and Abhijeet Shirsat. 2023. Emotions: The Unexplored Fuel of Fake News on Social Media. In *Fake News on the Internet*. Routledge. Num Pages: 28.

Matthew J. Hornsey, Kinga Bierwiaczonek, Kai Sassenberg, and Karen M. Douglas. 2023. Individual, intergroup and nation-level influences on belief in conspiracy theories. *Nature Reviews Psychology*, 2(2):85–97.

Elizabeth E. Housholder and Heather L. LaMarre. 2014. Facebook Politics: Toward a Process Model for Achieving Political Source Credibility Through Social Media. *Journal of Information Technology & Politics*, 11(4):368–382. Publisher: Routledge _eprint: https://doi.org/10.1080/19331681.2014.951753.

A. K. M. Najmul Islam, Samuli Laato, Shamim Talukder, and Erkki Sutinen. 2020. Misinformation sharing and social media fatigue during COVID-19: An affordance and cognitive load perspective. *Technological Forecasting and Social Change*, 159:120201.

Jessica Johnson. 2018. The Self-Radicalization of White Men: "Fake News" and the Affective Networking of Paranoia. *Communication, Culture and Critique*, 11(1):100–115.

Wandeep Kaur, Vimala Balakrishnan, Omer Rana, and Ajantha Sinniah. 2019. Liking, sharing, commenting and reacting on Facebook: User behaviors' impact on sentiment intensity. *Telematics and Informatics*, 39:25–36.

M. Laeeq Khan. 2017. Social media engagement: What motivates user participation and consumption on YouTube? *Computers in Human Behavior*, 66:236–247.

Jan Kirchner and Christian Reuter. 2020. Countering Fake News: A Comparison of Possible Solutions Regarding User Acceptance and Effectiveness. *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW2):1–27.

Gaurav Kumar, Rishabh Joshi, Jaspreet Singh, and Promod Yenigalla. 2020. AMUSED: A Multi-Stream Vector Representation Method for Use in Natural Dialogue. In *Proceedings of The 12th Language Resources and Evaluation Conference*, pages 750–758, Marseille, France. European Language Resources Association.

Ugo Laquièze. 2025. #LGBTpropaganda #GenderTheory #Wokism: Expanding and blurring the boundaries of francophone anti-gender discourse propagated on Twitter. *Politikon: The IAPSS Journal of Political Science*, 59(1):88–114.

Becca Lewis and Alice E. Marwick. 2017. Media Manipulation and Disinformation Online. Technical report, Data & Society. Publisher: Data & Society Research Institute.

Neil MacFarquhar. 2016. A Powerful Russian Weapon: The Spread of False Stories - The New York Times.

Guri Nordtorp Mølmen and Jacob Aasland Ravndal. 2021. Mechanisms of online radicalisation: how the internet affects the radicalisation of extreme-right lone actor terrorists. *Behavioral Sciences of Terrorism and Political Aggression*, 0(0):1–25. Publisher: Routledge _eprint: https://doi.org/10.1080/19434472.2021.1993302.

An Nguyen and Daniel Catalan-Matamoros. 2020. Digital Mis/Disinformation and Public Engagment with Health and Science Controversies: Fresh Perspectives from Covid-19. *Media and Communication*, 8(2):323–328.

An Nguyen and Daniel Catalan-Matamoros. 2022. Anti-Vaccine Discourse on Social Media: An Exploratory Audit of Negative Tweets about Vaccines and Their Posters. *Vaccines*, 10(12):2067.

Blair Nonnecke and Jennifer Preece. 1999. Shedding light on lurkers in online communities. *Ethnographic studies in real and virtual environments: Inhabited information spaces and connected communities, Edinburgh*, 123128.

Observatory on Social Media. Botometer X.

Jenny Preece, Blair Nonnecke, and Dorine Andrews. 2004. The top five reasons for lurking: improving community experiences for everyone. *Computers in human behavior*, 20(2):201–223. Publisher: Elsevier.

Neha Puri, Eric A. Coomes, Hourmazd Haghbayan, and Keith Gunaratne. 2020. Social media and vaccine hesitancy: new updates for the era of COVID-19 and globalized infectious diseases. *Human Vaccines & Immunotherapeutics*, 16(11):2586–2593.

Ignacio Ojea Quintana, Ritsaart Reimann, Marc Cheong, Mark Alfano, and Colin Klein. 2022. Polarization and trust in the evolution of vaccine discourse on Twitter during COVID-19. *PLOS ONE*, 17(12):e0277292. Publisher: Public Library of Science.

Madhavi Reddi, Rachel Kuo, and Daniel Kreiss. 2023. Identity propaganda: Racial narratives and disinformation. *New Media & Society*, 25(8):2201–2218. Publisher: SAGE Publications.

Sven Reichardt, editor. 2022. *Die Misstrauensgemeinschaft der "Querdenker": die Corona-Proteste aus kultur- und sozialwissenschaftlicher Perspektive*, sonderausgabe für die bundeszentrale für politische bildung edition. Number Band 10857 in Schriftenreihe. Bundeszentrale für Politische Bildung, Bonn.

Stephen D. Reicher and Alexander S. Haslam. 2016. Fueling Terror: How Extremists Are Made. *Scientific American*.

Bashir Sa'ad Abdullahi and Habeeb Idris Pindiga. 2023. Tracking the Diffusion of Disinformation on the SDGs Across Social Media Platforms. In Jan Servaes and Muhammad Jameel Yusha'u, editors, *SDG18 Communication for All, Volume 2: Regional Perspectives and Special Cases*, pages 145–174. Springer International Publishing, Cham.

Hyunjin Seo and Robert Faris. 2021. Comparative Approaches to Mis/Disinformation| Introduction. *International Journal of Communication*, 15(0):8. Number: 0.

Guosong Shao. 2009. Understanding the appeal of user-generated media: a uses and gratification perspective. *Internet Research*, 19(1):7–25. Publisher: Emerald Group Publishing Limited.

Kate T. Simms, Sharon J. B. Hanley, Megan A. Smith, Adam Keane, and Karen Canfell. 2020. Impact of HPV vaccine hesitancy on cervical cancer in Japan: a modelling study. *The Lancet. Public Health*, 5(4):e223–e234.

Bonnie Stabile, Aubrey Grant, Hemant Purohit, and Kelsey Harris. 2019. Sex, Lies, and Stereotypes: Gendered Implications of Fake News for Women in Politics. *Public Integrity*, 21(5):491–502. Publisher: Routledge _eprint: https://doi.org/10.1080/10999922.2019.1626695.

Henri Tajfel and John C. Turner. 2004. *The Social Identity Theory of Intergroup Behavior*. Political psychology: Key readings. Psychology Press, New York, NY, US. Pages: 293.

Joshua A. Tucker, Andrew Guess, Pablo Barbera, Cristian Vaccari, Alexandra Siegel, Sergey Sanovich, Denis Stukal, and Brendan Nyhan. 2018. Social Media, Political Polarization, and Political Disinformation: A Review of the Scientific Literature.

John C. Turner. 1991. *Social influence*. Social influence. Thomson Brooks/Cole Publishing Co, Belmont, CA, US. Pages: xvi, 206.

Jan-Willem Van Prooijen and Mark Van Vugt. 2018. Conspiracy Theories: Evolved Functions and Psychological Mechanisms. *Perspectives on Psychological Science*, 13(6):770–788.

Jan-Willem Van Prooijen and Karen M. Douglas. 2018. Belief in conspiracy theories: Basic principles of an emerging research domain. *European Journal of Social Psychology*, 48(7):897–908.

Martijn van Zomeren, Tom Postmes, and Russell Spears. 2008. Toward an integrative social identity model of collective action: A quantitative research synthesis of three socio-psychological perspectives. *Psychological Bulletin*, 134(4):504–535. Place: US Publisher: American Psychological Association.

Salvatore Vilella, Alfonso Semeraro, Daniela Paolotti, and Giancarlo Ruffo. 2022. Measuring user engagement with low credibility media sources in a controversial online debate. *EPJ Data Science*, 11(1):1–23. Number: 1 Publisher: SpringerOpen.

Lorella Viola. 2025a. What about Language? A Multilingual Behavioural Study of User Engagement with Disinformation on X: 5th Workshop on Reducing Online Misinformation through Credible Information Retrieval, ROMCIR 2025. *ROMCIR 2025 Reducing Online Misinformation through Credible Information Retrieval 2025*, pages 54–69. Publisher: CEUR-WS.

Lorella Viola. 2025b. 'Barren lesbians plotting sterilization': gender stereotypes and prejudices in health disinformation narratives, a cross-cultural analysis of social media of the HPV vaccine. In Catherine Tebaldi, Alistair Plum, and Christoph Purschke, editors, *Conspiracy as Genre: Narrative, Power and Circulation*. Bloomsbury Academic, London.

Bradley Wiggins. 2023. 'Nothing Can Stop What's Coming': An analysis of the conspiracy theory discourse on 4chan's /Pol board. *Discourse & Society*, 34(3):381–398. Publisher: SAGE Publications Ltd.

Florian Wintterlin, Tim Schatto-Eckrodt, Lena Frischlich, Svenja Boberg, Felix Reer, and Thorsten Quandt. 2023. "It's us against them up there": Spreading online disinformation as populist collective action. *Computers in Human Behavior*, 146:107784.

Asami Yagi, Yutaka Ueda, and Tadashi Kimura. 2024. HPV Vaccine Issues in Japan: A review of our attempts to promote the HPV vaccine and to provide effective evaluation of the problem through social-medical and behavioral-economic perspectives. *Vaccine*, 42(22):125859.

Kai-Cheng Yang, Francesco Pierri, Pik-Mai Hui, David Axelrod, Christopher Torres-Lugo, John Bryden, and Filippo Menczer. 2021. The COVID-19 Infodemic: Twitter versus Facebook. *Big Data & Society*, 8(1):20539517211013861.

8 Appendix

Table 7: data-set description

Value	**Count**
Likes	26,007
Quotes	1,281
Replies	3,329
Retweets	15,693
Users	2,091
Mentions	1448
Hashtags	13,691

Table 8: Call-to-Action Expressions by Language and Totals

EN	**ES**
wake, resist, join, sign, take action, act, must, do not comply, resistthereset, stop, share, help, demand, make, stand, stand up, speak out, raise your voice, get involved, take a stand, participate, march, protest, mobilize, defend, spread the word, volunteer, organize, boycott, take part, engage, rally, fight back, join the movement, act now, donotcomply	despierta, resiste, únete, firma la petición, actúa ahora, comparte, movilízate, haz algo, noalaagenda2030, noalplan, detente, toma, actúa, firma, ayuda, exige, haz, mantente, levántate, alza la voz, participa, actúa ya, protesta, lucha, defiende, propaga el mensaje, voluntario, organiza, boicotea, toma parte, únete al movimiento, comprométete, alístate, actúa hoy, únete ahora, haz tu voz escuchada, súmate, movilízate hoy

	EN	**ES**
en tweets	215	7
es tweets	3	92

Table 9: Seed Hashtags with corresponding number of tweets in the data-set

Hashtag	Count
#Agenda2030	2950
#agenda2030	336
#WEF	291
#ClimateScam	147
#GreatReset	144
#NWO	121
#NewWorldOrder	112
#Agenda2030.	90
#AGENDA2030	82
#NOM	76
#nwo	68
#Agenda2030,	66
#Agenda21	66
#Plandemia	65
#DigitalID	61
#ODS	58
#KlausSchwab	57
#DiedSuddenly	56
#15minutecities	55
#CBDC	50
#DepopulationAgenda	50
#climatescam	48
#cbdc	45
#chemtrails	44
#BillGates	42
#SocialCreditSystem	42
#PureBlood	40
#WEFpuppets	38
#billgates	34
#Globalist	32
#ClimateCult	32
#SDGs	30
#TheGreatReset	29
#Bilderberg	28
#Repentinitis	28
#NuevoOrdenMundial	27
#VaccineGenocide	27
#FBI	26
#wef	26
#GeorgeSoros	26
#vaccine	25
#plandemia	25
#ESG	25
#HunterBiden	24
#WEF2030Agenda	24
#repentinitis	23
#klausschwab	23
#WEFpuppet	22
#noalaagenda2030	22
#malditaagenda2030	22
#Fauci	22
#depopulation	21
#NetZero	21
#DictaduraSanitaria	20
#Soros	20
#CrimesAgainstHumanity	20
#Agenda2030?	20
#CBDCs	19
#vaccineinjuries	18
#CIA	18
#agenda21	18
#FueraONU	17
#WorldEconomicForum	17
#Nuremberg2	16
#Chemtrails	16
#15MinuteCities	15
#Jarnac	15
#VaccineSideEffects	14
#CambioClimatico	14

Topic ID	Count	Top Representative Terms	Representative Example (excerpt)
0	1689	agenda2030, nwo, video, com, world, order, people, global, reset, truth	"Immortalized cell lines used in lab-grown meat... global elites want to control the food supply."
1	362	chile, españa, onu, méxico, argentina, política, gobierno, países, sociedad, latinoamérica	"Y ahora @GiorgioJackson, @gabrielboric... hablan de la ONU y la Agenda2030 en Latinoamérica."
2	292	climatescam, climate, agenda2030, globalwarming, wef, co2, fake, scam, science, propaganda	"Desmintiendo el calentamiento global bufones de la ONU... ClimateScam."
3	46	canada, canadians, trudeau, agenda2030, climate, policy, protest, covid, freedom, rights	"Canadians need to support Alberta Oil & Gas — Trudeau is destroying our economy for Agenda2030."
4	37	vaccine, covid, depopulation, populationcontrol, health, agenda, wef, control, elite, world	"Vaccines are part of the depopulation agenda — open your eyes."
5	26	climatechange, greenagenda, sdgs, un, sustainability, policy, leaders, summit, goals, development	"The UN Climate Summit pushes Agenda2030 — same green agenda with new branding."
6	19	esg, economy, finance, corporations, capitalism, elites, governance, power, wef, global	"ESG is just a corporate version of Agenda2030 — economic control by the few."
7	16	energy, oil, gas, renewables, canada, europe, policy, crisis, cost, transition	"Energy transition in Europe is a scam — higher costs and less freedom."
8	14	digitalid, cbdc, surveillance, government, privacy, citizens, control, technology, freedom, rights	"Digital ID and CBDCs mean full surveillance — say no to control systems."
9	12	conspiracy, hoax, lies, fake, propaganda, media, agenda2030, truth, narrative, misinformation	"The media lies again — Agenda2030 is propaganda to hide the real plan."

Table 10: Full set of ten topics identified by BERTopic after multilingual preprocessing. Each topic shows its document count, most representative keywords, and a representative tweet excerpt.