Methodology Note: Social Media Analysis of Europe's Anti-Wind Ecosystem

May 2024 – February 2026

1. Overview

This document sets out the methodology underpinning the social media analysis published in *Wind Energy Dis- and Misinformation Undermining Europe's Security and Competitiveness*, produced by WindEurope in collaboration with CASM Technology. It is intended to support transparency by documenting the data collection, account annotation, classification, and analytical framing decisions that shaped the study. The analysis draws on 42,947 wind energy-relevant social media posts from 573 accounts, collected across Facebook, Instagram, X, YouTube, TikTok and LinkedIn between 1 May 2024 and 28 February 2026.

The dataset reflects the activity of known or suspected anti-wind actors, rather than a fully representative sample of all online discourse about wind energy. Patterns in actor composition by country or platform therefore reflect the scope and structure of the monitored sample, not necessarily the true distribution of European focused anti-wind activity online. Cross-country differences in posting volume and engagement are shaped not only by how many actors were identified in a given market, but also by the mix of actor types and platforms represented. Direct cross-market comparisons are less reliable, while specific country and platform contexts offer better comparability. While it is not possible to know the full scale of all social media activity online, based on the breadth of countries covered and the consistency of observed patterns, this network likely captures the core nodes of the publicly visible online anti-wind ecosystem across Europe.

Defining dis- and misinformation-related narratives
This study draws on the European Council's definitions of dis- and misinformation:[1]

> *Disinformation is false or misleading content that is disseminated with the intention of deceiving or seeking economic or political gains. It differs from misinformation, which is false or misleading information that is spread without harmful intentions.*

Since attributing intent from social media data alone is not feasible, this study focuses on the false or misleading nature of content and its potential impact, rather than on demonstrated intent. This is consistent with methodological practice in comparable studies of mis- and disinformation in mainstream media.[2] Both phenomena are therefore grouped under the term "dis- and misinformation-related narratives". This framing informs the classification framework set out in section 2.3.2.

The sections below document how accounts were selected, annotated, filtered, and classified to produce the dataset on which the report's findings are based.

2. Methodology

2.1 Data collection

Data was gathered through a combination of account-based and keyword-based collection methods. Data collection for selected platforms was supported through The Bright Initiative by Bright Data.[3]

Account-based collection
With input from WindEurope and its members, curated lists of accounts known or suspected to disseminate anti-wind narratives formed the core of the dataset. These seed accounts were used to carry out programmatic network expansion, identifying additional accounts and pages that interacted with or were linked to the original network. Expanded accounts were then manually reviewed for relevance before inclusion. The initial seed list comprised 881 accounts, though not all generated wind-relevant content during the collection period. The composition of the final dataset is described in section 2.3.1.

Keyword-based collection

[1] European Council, *Disinformation and Democratic Resilience*, https://www.consilium.europa.eu/en/policies/disinformation-and-democratic-resilience/, accessed 09 April 2026.
[2] Quota Clima, *Mapping Climate Disinformation in French and Brazilian Mainstream Media* (October 2025), https://quotaclimat.org/app/uploads/2025/10/Mapping-climate-disinformation-France-Brazil-medias-october-2025.pdf
[3] The Bright Initiative by Bright Data. https://brightinitiative.com/

Limited and targeted keyword searches on X and TikTok supplemented the account-based dataset. Content retrieved through this method was manually reviewed for relevance, though the majority fell outside scope and was excluded from further analysis.

2.2 Account annotations: actor categories, countries and languages

To facilitate downstream analysis, each account was manually reviewed and annotated against three key attributes:

- **Actor category:** Classified into one of six types, defined in the table below
- **Country:** Based on primary location or affiliation
- **Language:** Based on the top ten posts at the time of review

The final annotated dataset spans six actor categories, 25 country or affiliation labels, and 20 language communities. Volumes by category, country, and language are set out in the tables below.

Table 1. Actor categories, definitions, and volumes

Actor category	Description	No. of accounts	No. of posts
Activist	Individual actors seeking to shape public opinion on clean energy technologies, including wind energy.	93	5,476
Anti-wind group	Groups organised to shape public opinion on wind energy at local, national, or international level, with communications typically oriented toward direct political mobilisation.	236	33,514
Environmental group	Groups primarily focused on environmental issues that occasionally publish content opposing wind energy.	5	143
Lobby/Think tank	Organisations that seek to inform the public and/or policymakers on particular issues. Their communications typically aim to appear data-driven and analytical, with a focus on information and commentary rather than direct political mobilisation.	12	425
Media outlets & journalists	News organisations that regularly publish articles on a dedicated website, and individual journalists or commentators who regularly publish news-style content through such outlets.	78	2,435
Politicians & political parties	Individual politicians representing political parties in public communication, and political parties or affiliated entities competing in elections for public office.	84	954

Table 2. Posts and engagement by country

#	Country	Posts	Total engagement
1	Sweden	6,902	419,331
2	France	5,169	622,937
3	Norway	5,064	884,327
4	Finland	4,917	177,051
5	United Kingdom	4,853	1,100,089
6	Germany	4,680	928,114
7	Greece	1,650	428,553
8	Poland	1,437	540,706
9	Denmark	1,397	105,688
10	Netherlands	931	11,592
11	Austria	850	114,223
12	Spain	761	93,868
13	Latvia	709	160,613
14	Italy	701	182,213
15	Czech Republic	551	136,991
16	Slovakia	544	153,114
17	Bulgaria	436	141,440
18	Switzerland	424	12,692
19	Ireland	349	5,904
20	Belgium	268	3,277
21	Estonia	224	22,373
22	Slovenia	107	2,070
23	Portugal	11	2,456
24	Romania	10	40,216
25	EU	2	102

Table 3. Posts and engagement by language community

#	Language	Posts	Total engagement
1	Swedish	6,900	419,314
2	German	5,522	1,014,044
3	English	5,280	1,158,816
4	French	5,217	623,173

5	Norwegian	5,064	884,327
6	Finnish	4,857	176,834
7	Greek	1,650	428,553
8	Polish	1,437	540,706
9	Danish	1,351	53,341
10	Dutch	931	11,592
11	Spanish	761	93,868
12	Latvian	709	160,613
13	Italian	701	182,213
14	Czech	551	136,991
15	Slovak	544	153,114
16	Bulgarian	436	141,440
17	Estonian	224	22,373
18	Slovenian	107	2,070
19	Portuguese	11	2,456
20	Romanian	10	40,216

2.3 Data analysis

2.3.1 Filtering and translation

All collected data was filtered using a multilingual keyword list spanning 20 languages, developed to capture direct mentions and variations of wind energy-related terms. The final filtered dataset comprised 42,947 social media posts produced by 573 accounts, pages, and groups between May 2024 and February 2026. Of the 881 accounts in the original seed list, 308 did not generate posts included in the final dataset, either because they did not post wind-relevant content during the collection period, because relevant posts were not captured by the keyword filters, or because technical issues affected retrieval. All content was machine-translated to support cross-language comparison and downstream analysis.

2.3.2 Classification

In order to identify and analyse anti-wind narratives in the data, all wind-relevant posts were processed through a human-in-the-loop, LLM-assisted classification workflow. The process comprised two stages: claim classification and narrative mapping.

In the first stage, posts were assessed for alignment with mis- and disinformation-related content, defined operationally as false, misleading, or manipulative claims that distort public perception of wind energy. Since attributing intent from social media data alone is not feasible, this assessment focused on the nature and framing of content rather than on

demonstrated intent, consistent with the study's broader definitional approach set out above. Posts not meeting this threshold were captured separately and subsequently classified into the five non-dis/misinformation categories described below.

In the second stage, posts identified as containing dis- and misinformation-related content were subjected to narrative mapping using an LLM-assisted narrative discovery process, iteratively refined and validated by subject-matter experts. This produced 9 dis- and misinformation-related narrative categories, set out in the table below.

These classifications are used as analytical coding categories to organise recurring narrative patterns across actors, countries, and platforms. They should not be read as direct findings about the intent of any individual actor or post.

As a quality check, subject-matter experts reviewed a random sample of 20 posts from each of the nine mis- and disinformation-related narrative categories and assessed each post for consistency with the intended classification criteria. Across all classes, 83% of sampled posts were confirmed as containing a dis- or misinformation-related narrative. Agreement was highest for pollution and waste (100%) and health risks and safety hazards (95%), and lowest for technological unviability and foreign ownership and national security threats (75% each), where contested rather than clearly false claims are most prevalent. This review provided an indicative quality check rather than a systematic evaluation. As noted in the main report, individual posts do not necessarily articulate these claims explicitly, but consistently align with and reinforce broader narrative frames.

Table 4. Anti-wind mis-/disinformation-related narratives

Mis- and disinformation-related narratives	Description
Environmental destruction	Narratives that portray wind turbines as deeply harmful to nature and wildlife, creating the misleading impression that wind energy has a profound net negative impact on ecosystems
Economic failure	Narratives that frame wind projects as economically nonsensical, defying basic market logic.
Hidden interests, fraud and anti-democratic	Narratives that portray developers and supporters of wind projects as greedy actors willing to accept major environmental and social harm in pursuit of profit as well as an imposition by distant political or economic elites on unwilling local populations.
Technological unviability	Claims that wind power is technologically unviable, depicting turbines as destabilising, drastically

	increasing blackout risks, and failing to reliably supply households and industry.
Health risks & safety hazards	Allegations of serious health effects and operational dangers, often unsupported by evidence.
Foreign ownership & national security threats	Fears about foreign, especially Chinese, control, energy security, and exploitation.
Pollution, waste, & supply chain concerns	Claims about toxic chemicals, waste, and unethical or polluting supply chains.
Negative impacts on communities & heritage	Allegations of harm to rural areas, property values, tourism, and cultural sites.
Manipulation of research & advocacy	Accusations of fraudulent or manipulated research and advocacy.

To ensure the dataset captured the full range of anti-wind activity, and not only content characterised by dis- and misinformation, five additional classification categories were derived from the data. These categories cover oppositional content that does not make false or misleading claims, including mobilisation activity, procedural updates, and general opposition. Separating this content from misinformation-coded posts allows the analysis to distinguish between the spread of false claims and broader patterns of organised opposition.

Table 5. Anti-wind content: non-dis-/misinformation categories.

Oppositional theme	Description
Mobilisation & calls to action	Posts calling for action in opposition to wind energy. Includes petitions, protests, community meetings, fundraising appeals, film screenings, events, or submission guidance.
Procedural & policy coverage	Updates on planning, legislative, or regulatory processes including hearings, laws, rulings, or consultations.
Project announcements & developments	Announcements or factual descriptions of proposed, ongoing, or completed wind energy projects (new applications, construction, closures, etc.).

News & oppositional coverage	News reports, media links, or commentary that echo or highlight opposition or controversy without explicitly forwarding disinformation claims.
Oppositional sentiment	Emotive or personal statements opposing wind energy without claim-based content. Includes sarcasm, frustration, or aesthetic objections.

2.3.3 Engagement metrics

Engagement metrics are platform-specific and not always directly comparable across platforms. Like counts are available across all platforms; shares and reposts, which capture active redistribution of content, are available on Facebook, X, and TikTok; and views provide an additional measure of passive visibility on YouTube and TikTok.

To support more consistent cross-platform comparison, the analysis uses a unified engagement metric combining likes and shares or reposts. This is expressed as Engagement per Post (EPP), calculated as total likes plus shares divided by post count. EPP is used as a comparative measure of content performance across actors, themes, and platforms, and should be interpreted in relative rather than absolute terms.

2.4 Platform overview

Table 6 summarises posting and engagement patterns across the six platforms included in the dataset. These figures reflect the full collected dataset prior to any further filtering or segmentation applied in the main report.

Table 6. Platform volumes and engagement for anti-wind energy content (May 2024 – Feb 2026).

Platform	Posts	Accounts	Likes	Shares	Total Engagement	Views	EPP
Facebook	27,495	268	2,095,581	585,720	2,681,301	-	98
X	11,074	152	1,523,820	620,519	2,144,339	-	194
Instagram	3,549	55	760,693	-	760,693	-	214
YouTube	375	35	353,488	-	353,488	6,224,457	943
TikTok	413	51	295,217	53,239	348,456	9,031,896	844
LinkedIn	41	12	3,334	-	3,334	-	81

Note: EPP = (total likes + shares) ÷ post count. Shares were not available as a metric on Instagram, YouTube, or LinkedIn at the time of collection. View counts were only available for YouTube and TikTok.