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Attention and positive sentiments towards carbon dioxide removal have grown on social media over the past decade

Check for updates

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Scaling up CO2 removal is crucial to achieve net-zero targets and limit global warming. To engage with publics and ensure a social licence to deploy large-scale carbon dioxide removal (CDR), better understanding of public perceptions of these technologies is necessary. Here, we analyse attention and sentiments towards ten CDR methods using Twitter data from 2010 to 2022. Attention towards CDR has grown exponentially, particularly in recent years. Overall, the discourse on CDR has become more positive, except for BECCS. Conventional CDR methods are the most discussed and receive more positive sentiments. Various types of users engage with CDR on Twitter to different degrees: While users posting little about CDR pay more attention to methods with biological sinks, frequently engaged users focus more on novel CDR methods. Our results complement survey studies by showing how awareness grows and perceptions change over time.

All climate scenarios for keeping global warming to well below 2 °C warming rely on some form of carbon dioxide removal (CDR). While scale and deployment methods may vary, fast and substantial scale-up of CDR to several giga-tonnes by mid-century is required to limit global warming to stay within the Paris climate goals[1,2]. However, public perception of and support for new innovations has a strong influence on the political and economic feasibility of their widespread adoption[3–6].

It is now widely acknowledged that public attitudes will be crucial for the effective and ethical development and deployment of novel technologies, including CDR. The general public play many important roles, including determining policy mandates, paying for deployment via taxes, creating ‘demand pull’ for new innovations, acting as advocates or in direct opposition, and acting as direct stakeholders in local siting decisions[3,7].

Many CDR methods are not widely known to the majority of members of the public, with knowledge and awareness of CDR remaining persistently low in survey studies[1,8]. Therefore, public perceptions of these methods are in a formative phase and still subject to change[9]. Here, we complement the literature on public perceptions of CDR with a crucial, yet under-utilised, methodology, by analysing discourses on the social media platform Twitter.

Social media platforms provide an open space for various actors to share or shape their positions[10] and which facilitates, defines, and amplifies debates[11]. They can be crucial conduits where public information and perceptions of novel technologies becomes shared, with risk issues becoming potentially amplified or attenuated in the process[12]. Hence, it is particularly important to analyse policy-relevant discourses that might be picked up by news outlets or opinion leaders and thus impact debates beyond social media.

Here, we consider how different CDR methods are perceived by Twitter users, as it will influence the prospects of scaling them up[3,13–15]. Existing studies like these typically consider their dataset of Tweets as a whole without accounting for the fact that a small set of users with many Tweets may skew results of an analysis. To this end, we present a detailed analysis of the types of users posting about CDR on Twitter, to understand how reflective they might be of the wider public, and thus wider public debates. We do so by distinguishing users by frequency of mentioning CDR in their Tweets. Furthermore, we manually categorise a subset of users as firms, business people, communications, NGOs, policy, and private accounts.

Research on the public perceptions of CDR usually draws on quantitative data from representative surveys or choice experiments as well as qualitative data from focus groups, interviews or deliberative workshops. The vast majority of existing research on public perceptions of CDR is using survey methods[13,16–33], with a majority of studies on countries in Western Europe and North America[1]. The regions where public perceptions on CDR are studied least are often those where mitigation pathways suggest to scale-up the deployment of CDR the most[34,35]. Therefore there is a need to incorporate methods which can provide a more global picture of CDR perceptions. Studies find low levels of awareness and knowledge of most

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CDR methods in representative samples of the studied populations[13,15,34,36–41]. Factors such as trust in government, science and companies, beliefs about tampering with nature, and perceived trade-offs with other climate mitigation approaches are important determinants for people's initial reactions to CDR[42]. Deliberative studies find that attitudes toward novel CDR techniques can be cautious, conditional, and often ambivalent[13,15,43,44]. Amongst other things, some publics may be concerned that it only presents a provisional solution for high continued emissions[38,42,45,46]. However, evidence also shows that campaigns which try to improve 'acceptance' by improving public awareness of understanding (the so-called *information deficit* approach) can be ineffective and sometimes counterproductive[47,48].

Research on public perceptions should utilise a wide variety of methods to keep up with the rapid development of CDR[49]. Analysing historic social media data provides a complementary line of evidence to established social science methods in three ways: It allows retrospective analysis of existing data for almost any topic; it alleviates the challenge of studying the perception of technologies that are largely unknown to the public as individuals are sharing their non-elicited opinion; and it provides a higher temporal resolution than repeated large-scale surveys. Social media content is generated by people who are already aware of CDR and have a minimum level of prior knowledge on the topic and originated from a non-elicited motivation to publicly share a statement. We argue this kind of analysis can be particularly useful to gather early signals on how awareness and perception grow or later evolve. Especially for new and emerging technologies that are not yet well known among the broader population, there is typically already a large number of statements by people with a general awareness that can be analysed in a timely fashion[36,50].

Each line of evidence comes with their own benefits and limitations. Surveys and other deliberative methods offer researchers greater control over how and from whom evidence is collected at a particular point in time. But low public awareness of many CDR methods can lead to methodological challenges. For example, there is a risk of *framing effects* as a result of the way a question is presented or introductory information on the topic that participants received to base their response on. Data-driven analyses of social media content, on the other hand, allow researchers to track attention to a topic and sentiment towards it continuously over time, adjust research questions, and keep analyses updated. One of the main limitations is that the analysis is based on opinions from an essentially self-selecting group who may comprise a higher proportion of experts and those with a potentially vested interest in the topic. Therefore, we go beyond existing studies to empirically interrogate the proportion of users who fall into this category. The choice of platform will also influence the results, and is thus influenced by factors such as data availability. As such, we argue that social media analysis can provide a useful complement to other social science methods[51], rather than a replacement[52].

In this paper, we analyse past trends of debates around ten CDR methods on Twitter since 2010 and extend prior work[53] by comparing results for different user groups, including more recent data, and by scrutinising temporal developments. We pose the following research questions: What can we learn from social media data about perceptions of CDR? How do awareness and attitudes—as expressed by users online—change over time? And which types of users engage in CDR debates on social media? We use comprehensive keyword extraction based on expert inputs to retrieve posts about ten key CDR methods identified in the literature[54] and analyse them using machine-learning models for sentiment analysis. In this way, we provide novel insights, such as comparative tracking of attention and sentiment to CDR methods over time; showing that many users posting on CDR are not 'professional CDR communicators' or frequent tweeters, thus providing evidence in response to persistent concerns about Twitter analyses being strongly influenced by private interests; and linking findings from perception studies based on focus groups and questionnaires with high-resolution data from Twitter to illustrate how different lines of evidence integrate to form a more detailed understanding of public perceptions.

Results

Our analysis is based on 569,103 English-language tweets by 197,061 users that were retrieved using 54 method-specific queries[53] in the academic Twitter search API for ten CDR methods: *Conventional CDR* including soil carbon sequestration, ecosystem restoration, afforestation/reforestation, and blue carbon, as well as *novel CDR methods* including direct air capture (DAC, including DACCS), enhanced weathering, ocean fertilisation, ocean alkalinisation, biochar, and bioenergy with carbon capture and storage (BECCS). We also include a set of queries on general terminology related to greenhouse gas removal (GGR general) to capture the changing prevalent terms over time[55] and some communities prefering to use GGR as it refers a wider range of negative emission technologies. Throughout this article, we will refer to this set of queries as 'general GGR' to clearly distinguish it from the method-specific queries. Overall, our corpus of CDR tweets is small in comparison to the millions of tweets that directly mention 'climate change'[56].

Attention to CDR has grown exponentially, mainly driven by conventional CDR and general GGR topics

The overall growth is shown in Fig. 1 by the annual number of tweets per CDR method and the respective proportion. The CDR method mentioned in a tweet is determined based on the query that tweet was retrieved by. Attention to CDR was relatively low with less than 25k tweets per year until 2016, from where it grew to over 120k tweets annually, corresponding to a median annual growth rate of 32% (with standard deviation of 0.36). This growth is largely driven by a strong increase in tweets using general terms related to negative emissions. This is faster than the growth of tweets on climate change (28% annual growth on average) and even all English-language tweets on the platform (17%)[57].

We observe accelerating growth in attention towards CDR in recent years. In 2018 the annual growth in CDR tweets was 49%, and in 2019 59%. In 2020, the number of tweets slightly declines with the onset COVID-19 pandemic, similar to the wider climate-related discourse on Twitter[57–63]. In 2021, attention to CDR even grows by 76%, which is 62% of the pre-pandemic peak levels in 2019. Numbers remain at that level in 2022.

The vast majority of tweets (55% of all tweets; 77% excluding the GGR category) covers conventional CDR methods. Novel CDR methods, which are less developed, are only mentioned in 17% of all tweets (23% excluding GGR). Carbon capture and sequestration (CCS) is often confused with or mistaken for CDR, hence we do not include it in our analysis. For comparison, we retrieved 204,155 tweets, which would make up 14–30% of annual tweets in the extended corpus, and included respective numbers in Table 1.

The shift in attention provides evidence for the emergence of CDR as a substantive discourse in climate change mitigation. Throughout the beginning of the last decade, the overwhelming number of CDR tweets were technology-specific. The general discussion on GGR only emerged later and has become the largest individual discourse after 2017 (with the exception of 2019). This rapid growth of tweets referring to general GGR concepts, such as 'carbon dioxide removal', 'greenhouse gas removal', or 'negative emissions' coincides with growing recognition of the role for CDR in climate policy. It is important to note, that the growth of tweets on general GGR is on top of CDR-method-specific tweets.

The attention trends towards individual CDR methods vary substantively and is dominated by conventional CDR. 2019 has seen a stark increase in attention to afforestation/reforestation (30% of annual tweets) and ecosystem restoration (5–10%). The small proportion of tweets on novel CDR are mainly comprised of direct air capture with 5% of all tweets in the observed time-frame, whereas the proportion was strongest in recent years (up to 8%). BECCS and biochar, which together make up about 10% of all CDR tweets, are the second most mentioned novel CDR methods. Ocean fertilisation only briefly received any notable attention around 2012 (3318 tweets, 20% of tweets in 2012), but fell to very low levels after 2014 (540 tweets annually on average, 0–3% of annual tweets).

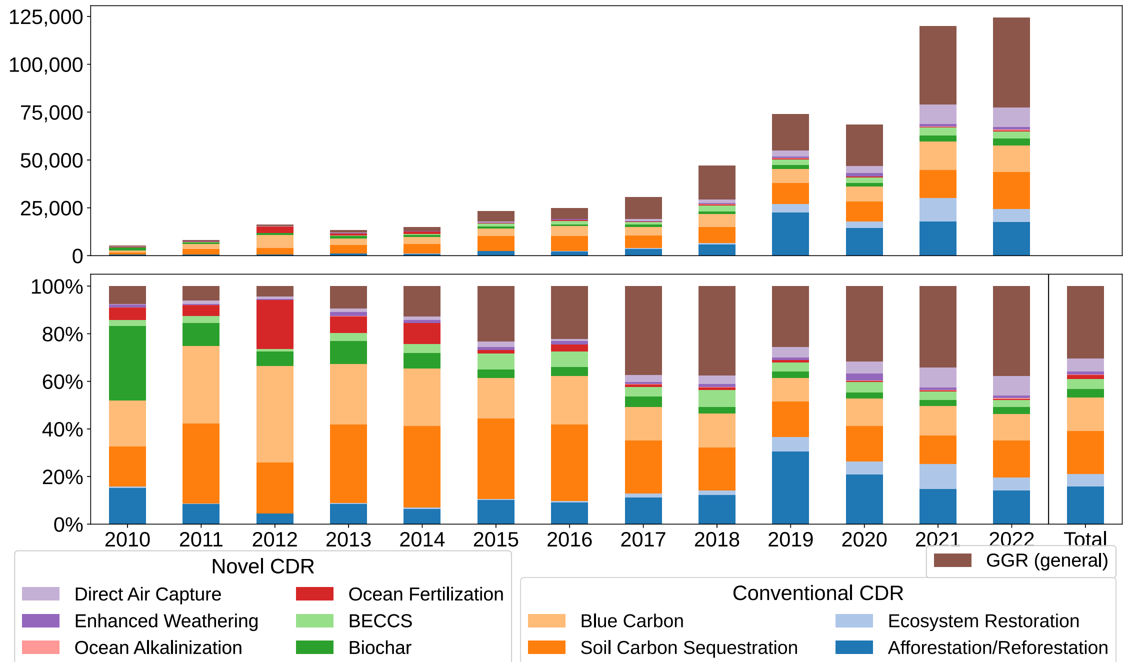


Fig. 1 | Tweet counts per CDR method per year. Top panel: Absolute tweet counts; Bottom panel: Share of tweets per year and overall.

Table 1 | Number of tweets by users with 1–2 (infrequent), 3–50 (moderate), and more than 50 (frequent) tweets in our corpus

CDR Method	Infrequent	Moderate	Frequent	All
GGR (general)	52,783 (−2%)	73,661 (−2%)	46,767 (+3%)	178,939 (32%)
Direct Air Capture	6354 (−11%)	13,996 (+1%)	11,059 (+11%)	32,087 (6%)
Enhanced Weathering	1530 (−11%)	2778 (−6%)	3,092 (+18%)	7514 (1%)
Ocean Alkalinisation	127 (−15%)	331 (− 2%)	340 (+19%)	807 (0%)
Ocean Fertilisation	4489 (+10%)	4732 (0%)	1350 (−11%)	11,071 (2%)
Biochar	4755 (−10%)	9639 (+ 1%)	7416 (+10%)	22,170 (4%)
BECCS	3247 (−17%)	9517 (− 2%)	10,159 (+20%)	23,227 (4%)
Blue Carbon	24,518 (− 2%)	39,414 (+ 4%)	17,373 (−3%)	85,207 (15%)
Soil Carbon Sequestration	26,420 (− 6%)	51,178 (+ 6%)	25,825 (+1%)	106,022 (19%)
Ecosystem Restoration	12,531 (+ 11%)	12,324 (− 2%)	4411 (−8%)	29,887 (5%)
Afforestation/Reforestation	43,054 (+ 15%)	35,187 (− 5%)	13,000 (−9%)	93,805 (16%)
Total	176,527 (31%)	243,240 (43%)	132,260 (23%)	569,103
CCS	*43,062 (− 10%)*	*90,035 (+1%)*	*65,209 (+9%)*	*204,155*
Methane Removal	*2124 (+ 17%)*	*1866 (0%)*	*284 (−17%)*	*4391*
Total (incl. CCS&MR)	*219,837 (29%)*	*329,312 (43%)*	*191,735 (25%)*	*763,800*

In parentheses, we show the deviation of the share of tweets per user group per technology from the share of tweets per user group overall ('Total' row). Numbers may not sum to the total shown, as tweet may cover more than one CDR method. CCS and Methane removal only shown for comparison. *Italic rows are only shown for reference and are not part of our analysis*.

Moderate and frequent users pay more attention to novel CDR methods than infrequent users, who focus more on biological sequestration methods

We assign users to one of three groups based on their respective total number of CDR tweets in our corpus. We perform a comparative analysis of different user groups, for which we split the dataset into tweets by *infrequent users* who only tweet once or twice about CDR, *moderate users* with up to 50 tweets on CDR, and *frequent users* with more than 50 tweets in our corpus. This allows us to distinguish patterns driven by users that are very interested in or familiar with the topic—possibly even over an extended period of time—and those that may be driven by external factors. These external factors may be news articles or announcements that prompted a large set of users to tweet about CDR once or twice.

The top 1% of users, frequent users with more than 50 CDR tweets, account for 23% of all tweets, moderate users for 43%, and infrequent users for the remaining 31% of CDR tweets (see Table 1 for tweet counts or Tables S4 and S5 in the supplemental material for user counts). We use the deviation of the proportion of tweets per CDR method by each user group from this baseline distribution as a measure of prevalent awareness and interest.

The number of tweets by infrequent users is well above the average for conventional CDR methods, in particular afforestation/reforestation (+15% above baseline; 46% of tweets on afforestation/reforestation are posted by infrequent users), ecosystem restoration (+11%; 42%), and ocean fertilisation (+10%; 41%). The number of tweets on blue carbon and general GGR are almost at baseline level (−2%; 29% each). The share of tweets by

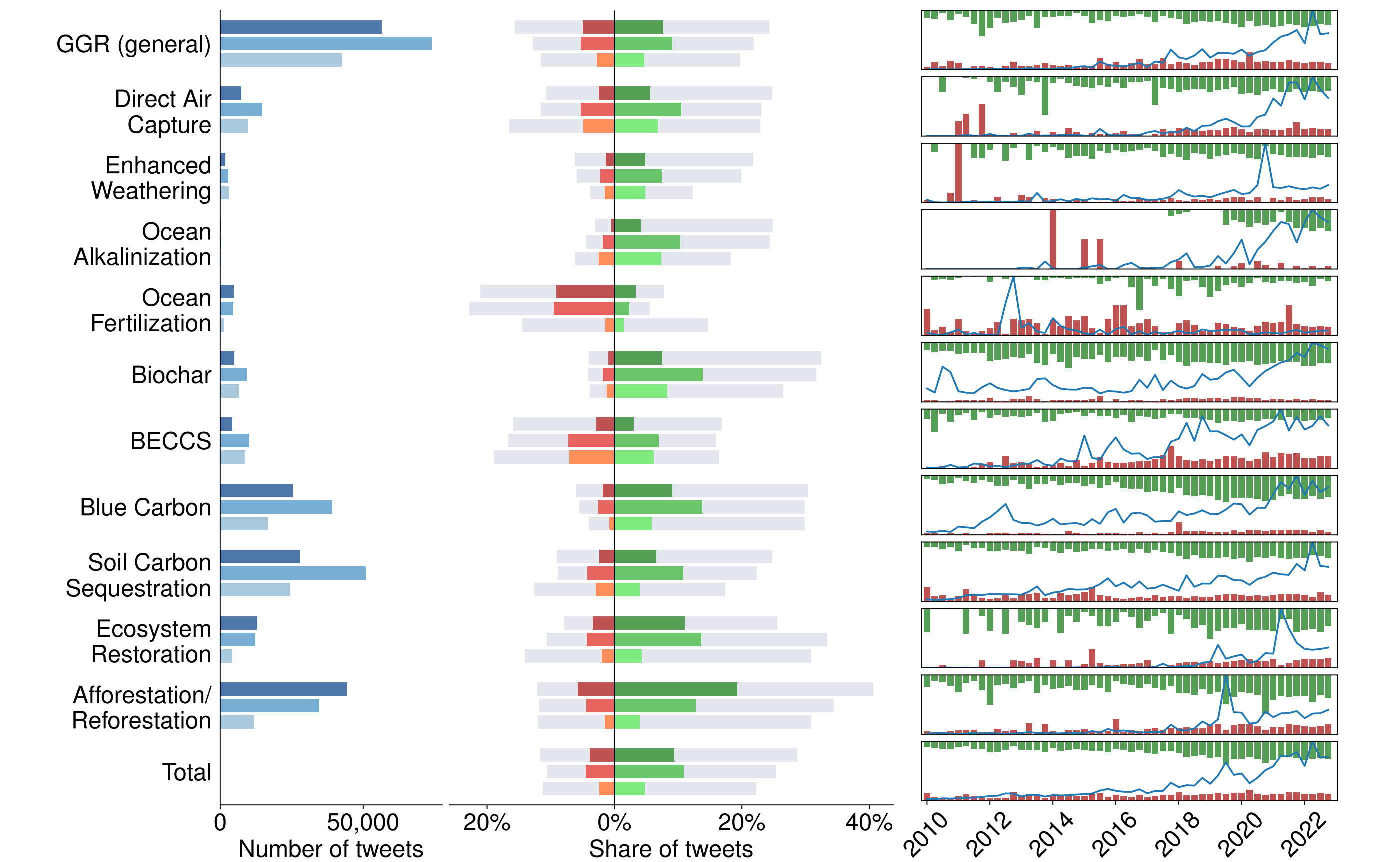


Fig. 2 | Sentiment in CDR tweets. Left panel: Number of tweets per CDR method and user panel, each triplet of bars refers to tweets by infrequent users (1--2 CDR tweets per user, darkest), moderate users (3–50 CDR tweets), and frequent users (over 50 CDR tweets, lightest). Bars for `Total' omitted for readability. Middle panel: Share of tweets with mainly negative (red shades, growing to the left) or positive (green shades, growing to the right) sentiment. Proportion is relative to the total number of tweets per method. Grey shade indicates the respective proportion relative to the number of tweets per method per user panel. Right panel: Share of tweets with mainly positive (green bars from the top) and negative (red bars from the bottom) sentiment over time (quarterly resolution, proportion relative to total number of tweets per method per quarter). White space in between reflects neutral tweets or missing data. Blue line plot shows the absolute number of tweets per method per quarter.

moderate users is very close to the baseline for all CDR methods. The proportion is highest for soil carbon sequestration (+6%; 48%) and blue carbon (+4%; 46%), and lowest for enhanced weathering (−6%; 37%) and afforestation/reforestation (−5%; 36%), showing no clear trend to favouring conventional or novel CDR. Frequent users, on the other hand, clearly dominate the conversation on novel CDR methods, most notably BECCS (+20%; 44%), enhanced weathering (18%; 41%), DAC (+11%; 34%), and biochar (+10%, 33%). They are slightly under-represented on the most popular conventional CDR methods, namely afforestation/reforestation (−9%; 14%) and ecosystem restoration (−8%; 15%).

These observations align with findings in survey studies that show higher awareness amongst participants of afforestation and restoration projects for carbon removal than for BECCS, enhanced weathering, or DAC[1,36,38]. Interestingly, these methods are those with the highest proportion of tweets by frequent users: BECCS (44% of BECCS tweets are from frequent users), enhanced weathering (41%), direct air capture (43%), and biochar (33%) and are amongst those that receive the lowest attention overall (less than 15% of all tweets). This suggests that the small group of frequent users are the main drivers behind the attention towards lesser known CDR methods. Similarly, better known CDR methods are picked up by a wider audience as exhibited by higher share of tweets by infrequent users and highest shares of infrequent users for these methods.

Conventional CDR methods are generally perceived more positively and ocean fertilisation the most negative

We automatically classify the sentiment, i.e. the tonality, of each tweet using pre-trained transformer models to count how often a CDR method is mentioned in a predominantly positive or negative context. We validated the sentiment classification by comparing several state-of-the-art pre-trained models and a dictionary-based approach to each other and with a manually annotated set of 400 CDR tweets (see methods). For most CDR methods and tweets with general GGR keywords the share of positive sentiments is larger than the share of negative sentiment, with the exception of ocean fertilisation, where negative sentiments prevail. The latter exception could be due to discussion over the effectiveness and negative side effects of ocean iron fertilisation after controversial field experiments[44,64]. Conventional CDR methods that are generally better known are mentioned most frequently in positive contexts, most notably afforestation/reforestation (37%, 12p.p. above average) and ecosystem restoration (29%). Biochar, blue carbon, and enhanced weathering are overall perceived most positively, because they have both high shares of positive tweets and the lowest shares of negative tweets. For novel CDR methods like BECCS and direct air capture, the share of negative mentions is higher, but still larger than the share of positive sentiments. Overall, 24.9% of all tweets have a positive sentiment and only 10.7% are classified with a negative sentiment.

Frequent users tend to communicate more neutrally than moderate and infrequent users

Figure 2 shows the share of tweets with positive and negative sentiments by user group. Infrequent users have the least number of neutral tweets with respect to their sentiment (60%), followed by moderate users (64%), and frequent users (67%). These differences are mainly due to varying shares of tweets with a positive sentiment, as the proportion of tweets with a negative sentiment are very similar for all groups (around 11%). This pattern holds true for many CDR methods. However, infrequent users tend to tweet most positively about biological sequestration methods such as afforestation/reforestation and ecosystem restoration. Biochar, blue carbon, and enhanced weathering are overall perceived most positively (highest shares of positive tweets with lowest shares of negative tweets). Ocean fertilisation is the only CDR method where frequent users have a higher share of positive and notably lower share of negative tweets than the rest. This is similar for enhanced weathering, except there frequent users have the lowest share of positive and negative tweets. These users that tweet most often about CDR appear to be more sceptical about direct air capture (16% of tweets by frequent users are negative, compared to about 11% for the others), soil carbon sequestration (12.6% vs. 9%), and BECCS (19% vs. 16%) than infrequent and moderate users, as their share of negative tweets is notably higher for each respective method. Ecosystem restoration presents the strongest differences in sentiments between all groups. Moderate users have the highest share of positive tweets (33%, 14% overall) and infrequent users the lowest share of positive tweets (26%, 11% overall). At the same time, frequent users have the highest share of negative tweets (13%, 2% overall) and infrequent users the lowest share (8%, 3% overall).

The share of positive tweets increases over time for most CDR methods, except for BECCS

On average, the number of tweets grows by a factor of 1.32 (median) each year. This growth factor does not deviate much year-to-year (standard deviation 0.36), but we observe highest growth factor leading into 2018 and 2019 with a temporary decline in 2020. Overall, the median growth factor of tweets with negative sentiment (1.49) is slightly higher than for positive (1.46), while the absolute number of negative tweets remains lower (there are 62,162 with negative and 143,530 tweets with positive sentiment). The growth factor for neutral tweets is slightly lower for infrequent users (1.25) than for moderate users (1.28) and frequent users (1.27). Across all groups, the number of tweets with negative or positive sentiment grows faster, on average, than for neutral tweets, but with a higher standard deviation (mean deviation for positive: 0.76, neutral: 0.43, negative: 0.71). The number of tweets with a positive sentiment by infrequent users and moderate users grows faster than for negative tweets (1.34 for positive vs. 1.32 for negative and 1.56 vs. 1.32). For frequent users, this trend is reversed (1.30 vs. 1.38).

As mentioned earlier, this still results in the same proportion of negative tweets (11–12% for all groups, grey bars in Fig. 2). The strong peak in attention to ocean fertilisation in 2012, was mainly driven by infrequent and moderate users and remains at a low level for all groups ever since. For all groups and CDR methods, the proportion of neutral tweets shrinks over time, suggesting that the public debate (on Twitter at least) may be becoming more emotional. We consider tweets on a method to become more polarised when the growth factor of tweets with positive or negative sentiment exceeds that of neutral tweets. Biochar and blue carbon are becoming more polarised across all user groups. For frequent users, soil carbon sequestration is also becoming more polarised. For infrequent and moderate users, afforestation/reforestation, BECCS, and GGR (general) show the same trend, and for moderate users additionally enhanced weathering. Overall, the net sentiment—the difference in daily shares of positive and negative tweets—is slowly growing at an average rate of 0.02% per day, except for tweets on BECCS (−0.01%).

Tweets by the top 1% of users have double the impact than those from users with only one or two tweets on CDR

Infrequent users (78% of all users), on average, posted 1.15 tweets, of which each, received 4.6 likes, was retweeted 0.4 times, and replied to 1.5 times. Moderate users (20% of all users) posted 6.1 tweets, and each tweet received 7.2 likes, was retweeted 0.5 times, and replied to 2.4 times on average. Tweets by frequent users (1% of all users), posted 101.1 tweets, where each on average received 10.5 likes, were retweeted 0.7 times and replied to 4 times. This shows that frequent users not only post more often, but each tweet received more likes, replies, and retweets than moderate users and double the amount than for tweets by infrequent users. Although infrequent users posted 31% of all tweets in the corpus, they only received 19% of all likes, 23% of replies, and 18% of retweets. Moderate and frequent users received more than double the absolute amount of likes and retweets. While moderate users posted 43% of all tweets, they received 43% of all likes and replies and 41% of all retweets. Frequent users posted 23% of all tweets and received 36% of all likes, 32% of replies, and 39% of retweets. This clearly shows, that posts by these users reach more people and are over-proportionally valued. For more details, see Table 1 or the appendix (Table S4 and Table S8).

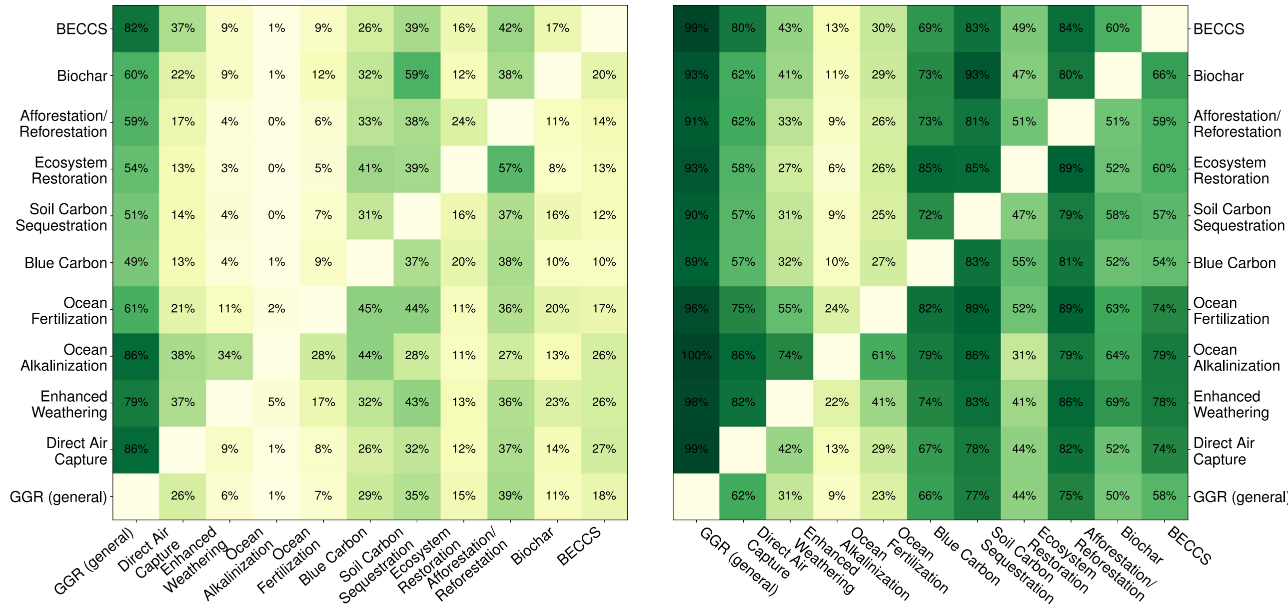
In order to get a better understanding of the user groups, we selected a random sample of 100 users from each group (300 in total) and had two annotators label those as firms, business people, communications, non-governmental organisations (NGOs), policy, private, or science based on the user name, handle and description (see Methods for further details). We find that a majority of users can be attributed to a specific category (74% of infrequent, 83% of moderate, and 87% of frequent users). The largest category are private accounts (17% overall), followed by communications (13%), non-governmental organisations (13%), business people (12%), firms (11%) and science (11%). The share for these categories per user group is very similar. Only 4% of users were categorised as policy-related. The share of private accounts decreases with increased number of tweets (20% of infrequent users, 17% of moderate, and 13% of frequent users), for businesses and business people, shares only very slightly decrease. Conversely, the proportion of frequent users categorised as NGOs (6%, 16%, 18%), science (8%, 10%, 15%), and communications (11%, 14%, 15%) grows with tweet frequency. This finding suggests that frequent user accounts are more often run by experts or (semi-)professional communicators.

The most common overlap in user attention are biochar and soil carbon sequestration as well as ecosystem restoration and afforestation/reforestation

We found that Twitter users that regularly tweet about CDR are interested in several topics. In order to analyse user attention across multiple methods, we count the number of tweets by users that tweet on each pair of CDR methods. These overlaps, normalised by the number of tweets on the method per row are shown in Fig. 3. As frequent users post more tweets than moderate users, the topical overlap is generally higher overall. Tweets on GGR in general have the highest overlap with all other topics, which is to be expected. This is followed by soil carbon sequestration, afforestation/reforestation, and blue carbon. To an extent, this effect can be attributed by the generally higher number of tweets on these CDR methods. Furthermore, tweets may refer to more than one CDR method and thus influence the aggregate counts. We account for these biases (see appendix for further details) and still observe a pronounced overlaps between several methods: There is a strong overlap in attention between ocean fertilisation, ocean alkalinisation, and enhanced weathering. These methods are similar in the sense that natural processes are artificially accelerated. Pronounced overlaps between BECCS and direct air capture as well as enhanced weathering and biochar reveal interest in a set of technologies for capturing CO_2 from airstreams or long-term storage on land.

Discussion

In this paper, we present an analysis of tweets on CDR and their sentiments as metrics for attention toward ten specific CDR methods and toward CDR in general. This is one means of understanding public mood toward these methods, and complements existing literature on perceptions of CDR which mostly uses other forms of data. Beyond providing insights into public perceptions, social media analyses capture and summarise the wide spectrum of arguments and opinions on a particular topic. Social media platforms provide an open space for various actors to share or shape their positions on potentially controversial topics[10]. This facilitates, defines, and amplifies (policy-relevant) debates[11], which are eventually picked up by news outlets and decision makers. To this end, it is especially important to monitor novel topics on social media, since the online discourse may influence political debates in the future. In the following, we discuss how our approach complements existing public perception research. We also discuss



(a) Users with 3–50 tweets (B)

(b) Users with >50 tweets (C)

Fig. 3 | Overlap of users with tweets on multiple CDR methods. Underlying absolute overlaps are symmetric (per pair of technologies, the number of users with at least one tweet on each technology), the shown relative overlap is normalised by the number of users per row (number of users per technology).

advantages and limitations of both social media analysis and other social science approaches to tackle these challenges.

With respect to our second research question on the time evolution, we find that attention to CDR on Twitter has increased strongly, driven mainly by conventional CDR methods and general CDR. Our results show that sentiment toward nearly all CDR methods, and CDR in general, is trending positively as awareness and engagement grows. This is an important insight because it suggests that public discourse is evolving gradually in a generally favourable way toward most CDR methods—important for understanding whether there is broad 'social licence' for policy-making in support of these techniques. That said, there are two exceptions to this trend. First, ocean fertilisation sentiment remains strongly negative over time, suggesting that great caution should be taken when considering whether to support it in policy[44]. Second, BECCS appears to be controversial and potentially polarising, with a gradual increase in negativity over the past 5 or so years and now equal shares of positive and negative sentiment. Thus BECCS proposals would likely benefit from additional context-specific research in the relevant locality, before decisions requiring public buy-in are made. Thus, timely tracking of these debates can help identifying early signals on how perceptions evolve. This can inform public engagement to ensure the rapid and socially accepted scale-up of climate solutions, such as novel CDR technologies.

We also investigated which types of users mention CDR in their tweets and whether the content they are posting differs. We find that a large variety of different types engages in CDR debates, from private accounts to business, science and NGOs. We also see that users tweeting more frequently about CDR tend to focus more on novel CDR methods, whereas infrequent users tweet more about conventional CDR methods. Frequent users are more often (semi-)professional communicators with a higher impact, measured by how many likes, retweets, and replies their tweets receive. However, counter to our expectations, a substantial proportion of tweets came from infrequent users. Most of the methods are tweeted about more often in a positive than in a negative context, with increasing tendency over time. Frequent users communicate more neutrally.

Our first research question is less straight forward, and in the following, we discuss different aspects of it regarding the alignment of our results with survey findings, specificities of emerging topics such as CDR, as well as implications of the particular user base and changes of the platform.

Aligning existing public perception literature with our analysis

Our analysis shows that social media analysis offers a complementary line of evidence to other social science methods that measure public perceptions of CDR methods, such as surveys, focus groups, or expert interviews. In the following, we compare our results to findings in this literature.

Studies of public perceptions have found that participants exhibit a preference towards CDR methods perceived as more 'natural', yet definitions of what constitutes as 'natural' are often vague. Respondents generally prefer familiar land-based methods (afforestation/reforestation in particular) over others[14,31,37,40,65,66]. This is reflected in our data, where the largest number of tweets are on afforestation/reforestation, soil carbon sequestration, and blue carbon, which also confirms findings from other Twitter-based studies[53,67]. Conversely, ocean-based CDR methods, ocean fertilisation in particular, are often perceived as most risky[40,50,68] due to their perceived uncontrollability and irreversibility[44,69]. This effect is expressed in our analysis by ocean fertilisation being the method with the highest share of tweets with a negative sentiment. However, frequent users, when compared to infrequent and moderate users, pay less attention to ocean fertilisation, have a much lower proportion of negative tweets, and the highest share of positive tweets on that method. This suggests that frequent users evaluate the risks involved differently compared to others. Surveys and expert interviews find that domain experts in CDR are often ambivalent when asked for their stance on specific CDR methods[70]. Assuming that frequent users have more expertise about CDR and some correlation between stance and sentiment, our Twitter dataset allows for a similar conclusion. Even though it is almost impossible to control for their level of expertise on a particular topic or the context that led them to share their opinion or a piece of information, the analysis of social media data is particularly useful to gather early signals on how awareness grows and perceptions evolve.

Twitter data as an indicator for people's 'awareness of' CDR

Twitter data, as such a large and global dataset, can fill gaps in knowledge relating to people's awareness of CDR methods, since the survey literature is geographically and temporally patchy[13,41]. Yet apart from some subtle differences, this global and longitudinal dataset broadly supports findings from existing national surveys. For example, we find more attention to more familiar land-based methods than novel methods[38,40]. In addition, enhanced weathering receives the second-lowest attention, in line with survey studies which find that people are particularly unfamiliar with this and other novel CDR methods[13,34,36,41]. That said, the analysis here was limited to English-language tweets, thus the similarity in findings may simply reflect the longstanding bias in public perceptions surveys to Western industrialised nations.

Interestingly, we do not observe strong variations in attention between different user groups, which may run counter to expectations, since we might expect the high number of 'don't know' responses in surveys to be reflected by a lower number of tweets on that method by infrequent users; yet we find that the distribution across user groups is fairly even.

Perceptions of topics with low prior knowledge

A key challenge for public perceptions research is the low awareness of many specific CDR methods and the need for scaling up CDR deployment to reach the Paris climate targets. For our social media analysis, this is manifested in a low number of tweets. For example, there are only few tweets on ocean alkalinisation, which caused some metrics to deviate more strongly. In surveys or interviews, low levels of awareness mean that participants often hear about CDR methods for the very first time when being asked. This may lead to framing effects: the answers that participants give can depend on how a technology was described to them by the survey. Careful study design tries to control for or minimise these effects and methods to un-frame public engagement have been explored[16,71].

Our results suggest that social media data does not just capture perceptions of experts, advocates or other interested parties, but also reflects the views of those who might have less day-to-day involvement with CDR, and can therefore be expected to have less prior knowledge. For example, 31% of tweets in our dataset come from users that only tweet once or twice and their tweet may have been provoked by some external factor, such as a news article. It is an open research question how familiarity might relate to user's sentiments and how different user groups shape the overall results.

Given the ubiquity of data analysis frameworks, it is very important to critically reflect whether a particular method is actually applicable in a way that allows robust and notable findings. Especially automated annotations using pre-trained machine learning models have to be verified on the dataset at hand. We manually annotated 400 tweets and compared several state-of-the-art pre-trained models and a dictionary-based model. Using these labels for validation, we selected the model from which we used the labels. We also found only a fair agreement between annotators, indicating how challenging this task is even for humans.

Understanding 'who' is surveyed

When comparing results across studies and approaches, it is important to consider the context and who's voice is actually included. In particular, there is no fixed definition of *the public* or who *interested parties* are. Social media constitutes one forum of public debate and can thus be seen as one of many publics. While it is very different from representative samples of a general population[72], both may be equally important for shaping future public perceptions on CDR, as public debates will influence opinions in the general population about the yet not very well known technologies. People also communicate differently depending on whether they are in a *professional* or *civic* role, which might change over time[7].

Surveys, experiments, and other deliberative approaches for elicited information operate within an artificial environment, allowing researchers to control and analyse the context. Usually, they aim to gather opinions from a representative sample of a general population, for example using recruitment quotas, and demographic variables to learn about explanatory factors for differences in the sample. At the same time, however, there is a clear trade-off between breadth and depth, with deliberative and discursive studies usually limited to fewer than 100 participants with low geographic dispersion, whereas survey studies can achieve sample sizes in the 1000s, but are often limited by resources to a defined geographic area (for instance, one or more countries)[1].

Our Twitter analysis, on the other hand, is based on almost 200 thousand users, of which 40 thousand tweet regularly about CDR and over 1000 posted more than 50 tweets on CDR in the observed time-frame. However, our approach leads to little control over whose voice is considered: The query strategy only includes English-language keywords and was only gathering data from Twitter (as opposed to multiple social media platforms). In this way, the underlying data will be biased toward countries with a larger proportion of English speakers, and toward the minority of the global population who use Twitter to more often publicly share their thoughts publicly on Twitter[72–74]. The data available through the academic Twitter API does not include demographic information—aside from self-reported geographic location of the users and tweets—to reliably quantify potential biases in that respect. Finally, it is worth noting that there is no way of conclusively validating whether the tweets analysed all came from real human beings. A recognised issue with Twitter analysis is the potential prevalence of bots (automated agents), which could skew the data[75,76]. We attempted to control for this by excluding tweets from exceptionally high-volume posters (see Methods and Appendix B). However, this issue again highlights that Twitter data should not be used as a straightforward proxy for public sentiment, but instead as a complementary method, for instance to flag emerging controversies so that more in-depth, targeted research can then be conducted.

Tracking perceptions over time

Repeating large-scale surveys or organising focus groups to track perceptions over time would be a very time-consuming and costly endeavour. In many cases, these factors are prohibitive for tracking changes in perception over time with (frequent) updates. To our knowledge, only one large-scale survey on CDR (BECCS, direct air capture, enhanced weathering) from 2012[28] was repeated in 2018[36]. Our analysis shows similar trends (see Fig. 1, Table S6), where attention to these three CDR methods is growing overall, but proportionally less than the other CDR technologies in our analysis.

The advantage of social media studies is that such analyses can be repeated cost-effectively to track the development of discussions. Furthermore, they can also be conducted retrospectively and at relatively fine-grained time resolution. In this way, the temporal granularity of social media data means that it can act as a sort of 'early warning' system for emerging controversies. However, although platforms such as Twitter may present themselves as neutral spaces, assumptions like that need to be specifically addressed and evaluated in scientific studies using social media data. In fact, the user base, interventions, and usage patterns are subject to constant change that might be long-term, but also contain short-lived 'viral' trends that can lead to disproportional biases in the results. Researchers have to account for such drifts and outliers in their analyses, for example by normalising temporal changes in Tweet frequency by the overall growth of Twitter and critically reflecting potential outliers or effects that may skew results.

The acquisition of the platform by Elon Musk and subsequent rebranding as 'X' introduced large uncertainties. The strong changes in platform policies in 2023 have lead to a a drastic shift in the user base[77,78]. This discontinuity makes it challenging to compare data from different time-frames and thus introduced large uncertainties over the continued use of Twitter as a consistent longitudinal indicator[77,78]. It remains to be seen how recent restrictions to access data on Reddit and Twitter will allow for continued research based on social media data[79]. Future work in this space needs to re-evaluate the basic assumptions about who uses the platform and the applicability to public perception research, including the development of new methods.

Towards using multiple complementing lines of evidence for public perception research

Given their different strengths and limitations, social media data and other social science approaches to study perceptions of CDR can complement and inform one another. Twitter data can provide longitudinal insights, which most other techniques cannot do, because repeating surveys and deliberative methods tends to be too costly and logistically complex. Surveys and focus group results have already been used in mixed-methods study designs for triangulating and complementing results[13]. Social media analyses could be integrated with established social science methods in similar ways: Surveys could be used as a way to inform the design of or calibrate social media analyses. For example, some survey results may open further questions that cannot be answered using the collected data. From this starting point, social media data could then be used to fill knowledge gaps by either collecting historical trends up to the point of the study or add details and context to selected aspects. Similarly, findings from a social media study could be used to inform the study design of a survey ahead of time. Another scenario to link approaches is to use social media data as a source for tracking trends at a higher resolution and perform conventional surveys to control for potential biases. There are similar potentials for enhancing public perception research in qualitative studies. For example, comments on surveys or statements from focus groups could be matched to posts on social media. There, responses or the context in which respective posts appear in may provide additional details and aspects. The number of views, votes, or replies to a particular statement might also inform researchers about whether the comment by a single respondent in a survey is supported by a wider audience. As these ideas for reciprocal stimulation show, future work can integrate these methodological approaches in different ways to further our knowledge about public perceptions of CDR.

Methods

In this work, we analyse a large set of 570k tweets on ten carbon dioxide removal (CDR) methods and greenhouse gas removal (GGR) in general. We further enrich the tweets with sentiment scores and categorise users by their characteristics. Finally, we compare the findings from our in-depth analysis with results of published survey studies.

Data procurement

The corpus[80] of 569,103 tweets by 197,061 users was compiled by querying the Twitter academic full-archive search API (v2) on January 16, 2023 with 54 queries (see Section Supplementary Notes 1 and Table S1 in the appendix) These queries are derived from a prior study on geoengineering on Twitte,r[53] and are based on a comprehensive set of keywords from the CDR literature[2,54] as well as feedback from experts. We appended `-is:retweet lang:en` to each query, so that results are limited to 'original' English-language tweets only.

The queries are grouped into ten CDR method categories and a category for general greenhouse gas removal terms. Each tweet is automatically annotated with the method category of the respective query. Most tweets (517,063; 91%) responded to queries from only one category, 43,485 (7.6%) to two categories, and 5654 (1.1%) to more than two categories. Although the first tweet on Twitter was posted on March 21, 2006, we did not match any CDR tweets before February 9, 2007; until the end of 2009, 7,066 tweets on CDR were posted. In light of the low relevance of the topic in the early years of the platform, we limit our analyses and reporting to the time period 2010 to 2022.

CDR method categorisation

We use the method-specific queries to tag tweets. Based on the query a tweet was retrieved by, the respective CDR method (or the general GGR category) is assigned. Note, that a tweet may have been retrieved by more than one query, even across different methods. In aggregations, we count only distinct tweets (by their Twitter ID) per method, but the same tweet might be counted for multiple methods.

User groups

Following our initial exploration of the corpus, we noticed several users who posted an exceptional amount of tweets, which are often even very similar. Based on a closer analysis of the distribution of the average number of tweets sent by a user per day and manually validating random samples, we determined this to be spam-like behaviour. Therefore, we exclude 17,076 tweets (3% of the corpus) by 2646 users (1.3%) who, on average, posted more than 100 tweets per day (see appendix for more detail).

Further, we categorise users based on their number of tweets in our corpus. This allows us to attribute findings to users that only posted one or two tweets on CDR in the entire 13 year time-frame ('infrequent users', $n = 153k$, 78%), tweet several times about CDR (3–50 tweets 'moderate users', $n = 40k$, 20%), and 'frequent users' who tweet very actively (more than 50 tweets, $n = 1308$, 1%).

The lower bound is based on the average number of tweets per user (2.89) across the entire corpus, so that the first group contains all below-average users. The upper bound is based on the 99th percentile of tweet counts per user to capture the top 1% of users who tweet on CDR.

Sentiment classification

We use sentiment scores, which refers the tonality of a written text, as a proxy of how well a given CDR method is perceived. Many studies based on social media data use the NRC lexicon[81,82] to compute scores based on the existence of keywords in the text. In this study, we rely on two state-of-the-art and more robust classifiers[83,84], that are pre-trained on large and widely used datasets[85,86]. These transformer-based classifiers are trained on tweets, even a subset of climate-related tweets, and other short texts. These classifiers are shown to perform very well on test data.

To verify the applicability of the pre-trained classifiers in our domain, we had three annotators label the sentiment (positive, negative, neutral) of 400 randomly selected tweets. Our inter-rater agreement (Fleiss' kappa) was $\kappa = 0.40$, which is only a slight to fair agreement. Given the large divergence in human annotations and results of both classifiers performing producing much more similar labels than human annotators, we decided to only report on the results of the classifier by Cardiff NLP[84] with results of the other classifier being essentially the same.

Manual user category annotation

In order to better understand who the users are, two annotators independently annotated 300 randomly sampled users, 100 from each user group. Each annotator was asked to assign each user based on their profile to one (or two) of the following categories: *firms* (official company and business association accounts), *business people* (individual users with central roles in corporations, advisors, self-employed or business owners), *communications* (news portals, journalists, and bloggers), *NGO* (official NGO accounts and proponents of social movements), *policy* (government accounts, officials, politicians and policy advisors), *science* (educational or research institutions, lecturers, students, and scientists), *private* (users that predominantly introduce themselves as private persons), and *other/unclear* (does not fit any other category or unclear or no description). In edge cases, annotators were allowed to add a secondary category. Inter-annotator agreement was moderate with a Cohen's kappa score of 0.54. When also counting matches with the secondary category agreement was substantial with a Cohen's kappa score of 0.67. For the final shares reported in the paper, the annotators resolved disagreements in a joint discussion. Table S2 in the supplemental material contains the number of users per category for each user group.

Systematic literature search

We carried out a systematic search of existing public perception research of CDR in the English-language academic databases Scopus and Web of Science. We found 39 papers on 'public perceptions', 'attitudes', or 'opinions' on CDR published before 2023[1]. Articles on related technologies, such as carbon capture and storage (CCS), bioenergy (without CCS), forestry, and ecosystem restoration, were only included if they specifically discuss those in the context of removing carbon as defined in this paper. The most common methods for assessing public perception of CDR include surveys, questionnaires, focus groups, interviews, and deliberative workshops. Articles solely relating to expert perceptions were not included.

Data availability

The Twitter corpus compiled for this publication is (in part) available on Zenodo[80] and can be accessed via this link: https://doi.org/10.5281/zenodo.10418701. Please note, that Twitter's terms of service do not permit sharing the full corpus, so the dataset is restricted to respective unique identifiers that can be used to hydrate the dataset using the Twitter API and our technology and sentiment annotations.

Code availability

The code to retrieve, classify, and otherwise enrich the data and to produce the tables and figures in this article is available on Zenodo[87] and can be accessed via this link: https://doi.org/10.5281/zenodo.13903735.

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