Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-023-02377-4 OPEN

Twitch as a privileged locus to analyze young people's attitudes in the climate change debate: a quantitative analysis

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Social media platforms are becoming an increasingly important venue for public debate. Twitch, in particular, is a popular streaming platform that targets young adults. Originally created for online video game players, the platform also includes other types of content, such as politics, leisure, and science. Here, we present a study that examines climate change discourse on this understudied platform. Unlike previous studies, this work does not only focus on users' reactions to streamer discourse but, using an ad-hoc methodology, also analyzes the content of the videos. Indeed, an added value of this research is the development of an objective evaluation based on automatic speech recognition (ASP) and natural language processing (NLP). We found that Twitch is an emergent locus for climate discussion with a thriving community of young users interested in the topic. Our findings challenge the understanding of social media discourse on climate change and suggest that platform architecture and intended commercial goals do not play a decisive role in shaping the topics circulating on them. In contrast, our findings support the idea that public discussion on climate change percolates through technology. In other words, the public debate finds its way across existing channels rather than being constrained by them. The research also contributes to the literature by expanding the empirical base for the study of online communication about climate change, especially among young audiences.

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Introduction

The inception of live-streaming platforms. In recent years, the emergence of streaming platforms has changed the way people socialize and keep themselves informed (Sveningsson, 2015; Connor et al., 2016). The lockdown imposed due to the COVID-19 pandemic accelerated the transition from traditional to new media based on social networks and streaming services (Chae and Lee, 2022). One of these new media services is *Twitch.tv*. Launched in 2011, Twitch has rapidly become one of the most significant entertainment providers, with more than 2.5 million concurrent viewers per month (on average). The platform was originally designed for the live streaming of video games but has now evolved into a new way of keeping informed on various topics, such as politics, leisure, lifestyle, science, and sports, among others (Spilker et al., 2020).

Like other digital-based companies, such as Facebook or YouTube, Twitch can be defined as a platform (Srnicek, 2017). Platforms are intermediary digital infrastructures that enable different user groups to interact. As intermediaries and infrastructure, platforms collect and control data through their core architecture (hardware and software; Neubauer et al., 2007) and shape how users interact. Platforms are not neutral spaces and can exert influence on many aspects of social practices, such as through user policy, marketing campaigns, and algorithmic content curation (Gillespie, 2010; Nieborg and Poell, 2018).

The rapid spread of Twitch may be explained by several factors: COVID-19, the decline of text-based social media, and monetization. The lockdown restrictions during the pandemic escalated the consumption of streaming services due to an increase in leisure time but also as an alternative to social isolation (Lemenager et al., 2021). For this reason, live streaming platforms have become an instrument to keep in touch with other people. Instead of text posting and chat rooms, there has been a rise in video streaming that is more apparent in younger audiences (Manavis, 2022). Additionally, unlike YouTube, Twitch offers more monetization options for content creators (Abarbanel and Johnson, 2020).

Twitch has three pillars: channels, content, and users. Channels are the individual spaces where streamers (also known as content creators) can broadcast their content. Content is the material that is being broadcast, such as games, music, or art. Users are the people who watch the content that is being broadcast (viewers or audience). As a business, Twitch has commercial goals to make the company economically profitable. These goals can be achieved by using different monetization strategies, such as subscriptions, donations, advertising, sponsorships, and merchandising. The revenue is shared between the streamer and Twitch, in percentages that vary depending on the streamer's popularity (Johnson and Woodcock, 2019).

The key feature distinguishing Twitch from other streaming services (e.g., YouTube) is the participative engagement of, and intense interactions between, streamers and their community (Ask et al., 2019). This is generated thanks to a simple but powerful combination of live video and text-based chat where viewers participate in real-time. The interface allows Twitch to be a place for discussion and exchange of opinions. As such, it can be used to investigate the climate change conversation among young audiences.

Climate change discussion on social media. Most research about climate change on social media is focused on a few platforms: Twitter, Facebook, and Reddit (Cann et al., 2021; Treen et al., 2022; Holder et al., 2023). Of that list, Twitter (now *X*) has been the preferred source to investigate a wide variety of subjects. Polarization, misinformation, and echo chambers are some of the most common topics that dominate the study of climate-related twittersphere (Treen et al., 2020; Chen et al., 2021b; Falkenberg et al., 2022; Sanford et al., 2021). The range of topics is varied. Some authors have investigated the role of language in the climate change debate while others have explored the importance of social bots in online discussions (Jang and Hart, 2015; Flottum, 2017; Chen et al., 2021a).

Threads on Reddit have also been studied. Shah et al. (2021) examined how three climate-related events influenced collective action measured in terms of the number of comments on the platform. In a recent paper, Treen et al. (2022) studied the polarization of the climate change discourse in this social media and the uniqueness of the platform for deliberative debate. Similarly, van Eck et al. (2020) used blog comments for the same purpose.

Other platforms, such as YouTube, have also been evaluated. For example, Shapiro and Park (2018) found that comments uploaded in post-video discussions were mainly dominated by a few "elite" users, who drove the discussion towards their own interests. In another study, Andersson (2021) analyzed comment threads in a sample of ten videos against Greta Thunberg's activism. A major problem with these works is that the research mostly focuses on user comments rather than the video content itself. An exception is found in Allgaier (2019), who watched and analyzed a sample of 200 videos on YouTube to assess whether they met the scientific consensus on climate change.

Overall, climate change discussion on Twitch has been the subject of scant study. There are several reasons for the lack of interest: novelty (twitch started operations in 2011 but only recently became a major player), misunderstanding about its relevance beyond the gaming culture, and the complexity of analyzing large amounts of video content. In the first case, the recent rapid growth has generated low research activity but a future expansion is expected. Furthermore, the popularity of Twitch has only reached certain age groups (16–24 and 25–39), which represent 83% of its total users according to the Global Web Index (www.gwi.com). A consequence is that scientists may consider the audience too narrow to be worth studying. A second reason might be that most of the research about Twitch has focused on gaming-related topics, such as community development, feelings, and mental health (Gandolfi, 2016; Consalvo, 2017; Seering et al., 2017; Woodcock and Johnson, 2019; Bingham, 2020; Wulf et al., 2020; Chae and Lee, 2022). Only a few studies have presented a broader understanding of the platform and used Twitch to answer more general research questions. For example, Ruiz-Bravo et al. (2022) showed how users have found ways to use gameplay to promote political activism, demonstrating Twitch's potential as a political space. Riddick and Shivener (2022) used Twitch to study the 'affective spamming', a visual-content-based form of spam that online audiences use to influence public communication and deliberation on social media during live events. In another work, Iranzo-Cabrera, Casero-Ripollés (2023) examined the role of Twitch as a locus for connective democracy and analyzed how social media are capable of potentially transforming politics and exercising power. Regarding communication, Spilker et al. (2020) explored how Twitch is changing the landscape of media communication by introducing the active engagement of the users. Similarly, Woodcock and Johnson (2019) argued that Twitch has revolutionized television by 'democratizing' who can create and share TV-like content. This has reduced the control that traditional media has over the content and the ideas shared and discussed in the public sphere. The third reason involves how to deal with large amounts of data. As a reference, our research included nearly 130 h of video streaming and more than 150 GB

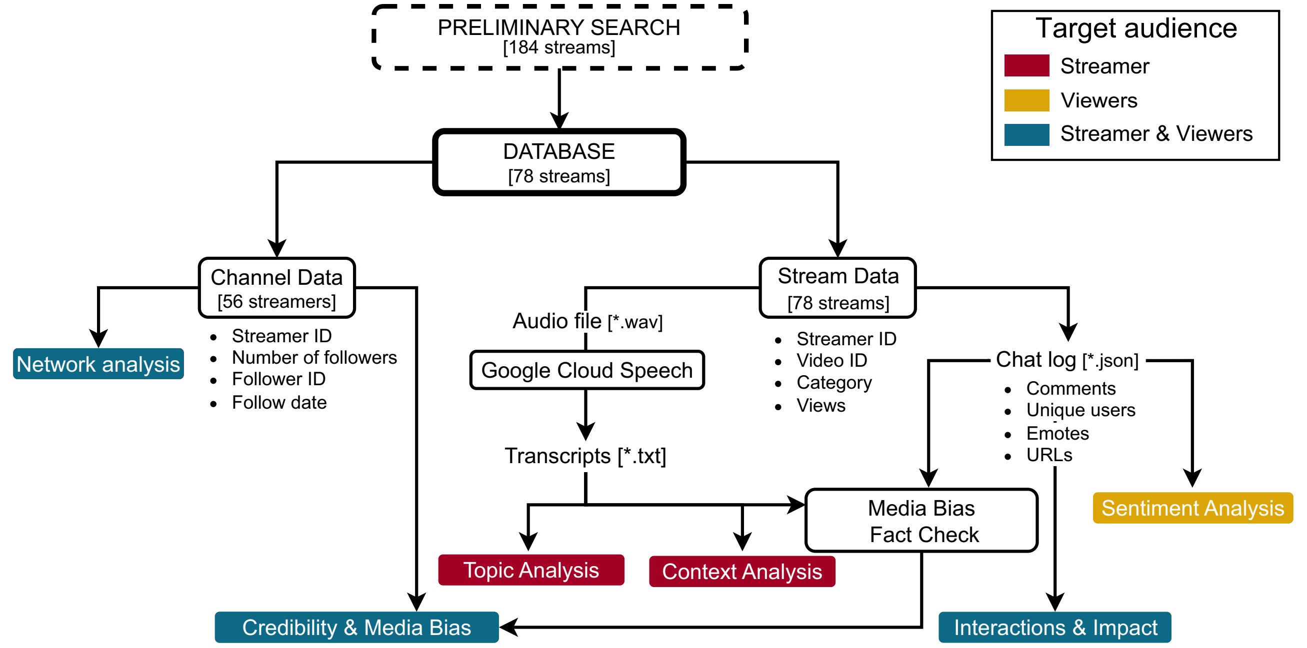

Fig. 1 Workflow diagram used in this research. All processes included in the flowchart are based on an objective analysis and are fully automated. The analysis tools are color-coded according to the target audience: streamers (red), viewers (yellow), and both (blue).

of data. Manual inspection would require large amounts of human resources and the results might not be satisfactory due to a number of biases. Using samples may be an alternative approach, but we could miss key information, as described by Kirilenko and Stepchenkova (2014). In order to overcome such hurdles and ensure reproducibility, computerized analysis is the appropriate tool to deal with large amounts of data within a relatively short time.

Here we present a quantitative, objective, analytical method to examine climate change discussion on Twitch. We used an objective evaluation based on automatic speech recognition (ASR) and natural language processing (NLP) for this purpose. The study analyzed all the available video streams (78 at the time of the research) and their associated chat logs, as well as other quantitative data about streamers and subscribers. Therefore, the novelty of this work is not restricted to the evaluation of a new platform or to the results of the analyses but also includes the methodological approach (an objective, repeatable, automatic evaluation) for the analysis of the video content. This new approach to extracting, processing, and analyzing combined data from text and video presents an ad hoc methodology that departs from the conventional framework established in previous research on social media. Our main aim is to provide a better characterization of the climate change discourse on social media, a topic of clear interest for the scientific community as regards climate emergency mitigation and adaptation.

Data and methods

Data collection and pre-processing. We used the terms “climate change” and “global warming” as keywords for scraping videos from Twitch. We obtained 184 entries, which were reduced to 78 after a cleaning-up process. The filtering consisted of removing duplicates (2), unavailable (29), and unrelated (63) videos. Additionally, we removed videos with fewer than 5 views (12) to ensure that they had enough impact on the community. The search for this paper was conducted on September 9, 2022. An important limitation is that past broadcasts are saved for a limited time (14–60 days), varying according to the type of content and subscription. The selected videos were broadcast from June to September 2022.

The sample was comprised of 56 streamers. 73.1% were male and 26.9% female. No quantitative information about age was obtained but most of them ranged from 18 to 50 years. 89.1% of streamers broadcast alone while 10.9% with collaborators/colleagues. The most common content was games (39.3%), followed by news and politics (26.8%), science and education (17.9%), art and music (10.7%), and economy (5.4%). Regarding ‘professionalization’, 21.4% are partners (full-time job), 53.6% are affiliated (part-time job) and 25% are standard members.

All the data was processed using Python Twitch API (https://pypi.org/project/twitchAPI/), except video title scraping, which is not implemented in the original API. For that purpose, we used the Apify platform (https://apify.com). We downloaded, extracted, and processed the audio of each stream as well as their associated chat log. Audio files were transformed into text using Google Cloud Speech API. The flow chart (Fig. 1) shows the overall methodology used to collect and process the data.

Network analysis. We identified 56 unique streamers from the list of 78 videos (Table 1). We obtained the follower list for each streamer and performed the network analysis using the NetworkX Python package. We constructed an adjacency matrix where nodes are streamers and edges represent “shared” followers. We found four isolated streamers, which were removed from the matrix to avoid the issue of network fragmentation. Since these streamers did not contribute to the connectivity of the network, removing them made the network easier to visualize and analyze. No weights were assigned to edges, and a low threshold of 1 shared follower was necessary to capture all of the connections in the network. The resolution parameter was optimized to find a set of communities that was both manageable and meaningful while preventing micro-communities of 1–2 members.

We applied Louvain’s algorithm to extract the community structure of the network (Blondel et al., 2008). This method is based on modularity optimization, and, to maximize the modularity, the algorithm has two iterative phases. The first phase assigns each node in the network to its own community. It

Table 1 List of channels included in this study.

Streamer ID	Followers (total)	Followers (shared)	Videos	Chat
91693482	6268	3804	1	Yes
29508146	423	15	1	No
603038896	9	0	1	No
71525808	36	13	1	No
245833207	851	127	2	Yes (1/2)
268390810	124	9	2	Yes (1/2)
474834851	1492	492	1	Yes
257325538	1302	300	1	Yes
553507359	643	33	1	Yes
111462736	391,786	1216	1	Yes
543901675	107	3	2	Yes (2/2)
26605147	37,280	1895	13	Yes (13/13)
243140019	63	1	1	Yes
547528048	970	12	1	No
24687283	110,142	2815	1	Yes
93954918	1744	67	1	No
413808408	10	0	1	No
52415737	7818	1419	8	Yes (8/8)
42517244	292	11	1	Yes
35759863	47,000	8065	1	Yes
78986931	24,331	7732	1	Yes
38151986	321	12	1	Yes
223836682	48,559	1462	1	Yes
64779677	7308	126	1	Yes
547499765	23	2	1	No
671315666	3595	619	1	Yes
678972593	91	17	1	No
277041888	199	8	1	Yes
506893280	191	30	1	Yes
489730711	204	3	1	Yes
569544149	289	7	1	Yes
199074049	62	0	1	No
188455984	5167	1419	1	No
88513287	572	36	1	Yes
603027481	157	3	1	Yes
593765551	37	2	1	Yes
271693404	217	5	1	No
475481040	287	2	1	Yes
263366813	875	36	1	Yes
101644689	7719	3747	1	Yes
101238569	10,438	2360	1	Yes
604740351	291	193	1	Yes
746516362	51	10	1	Yes
255051676	7	0	1	No
9238003	467	43	1	Yes
249594082	1882	78	1	Yes
507752714	903	34	1	Yes
403931423	746	198	1	No
76085942	17,713	370	1	Yes
404597642	2907	179	1	Yes
107437992	3551	255	1	Yes
511515718	1283	874	1	No
609529855	11	2	1	No
19230969	23,474	333	1	Yes
23336595	13,041	379	1	No
188548	4081	196	1	Yes
Total			78	59

The third column is the number of followers in common with other streamers. The fourth column represents the number of videos analyzed for each streamer. The fifth column shows whether the chat is active during the streaming.

then seeks to maximize modularity gain by merging communities together. Both phases are executed until there is no possible modularity gain from merging communities together. The algorithm has been used to successfully detect communities in complex networks and is currently one of the most popular in network analysis due to its simplicity and efficiency (Petersen et al., 2019; Vu et al., 2019; Williams et al., 2015). It is worth noting that each user can only belong to a single community.

For interaction between communities, we calculated the assortativity coefficient r (Newman, 2003). It assumes that nodes within the same category are more likely to be connected to each other than nodes in different categories. The value r lies between -1 and 1. Positive values mean that nodes of the same category tend to be connected with a higher probability than expected (assortative/homophile), while negative values mean that dissimilar nodes tend to be connected (disassortative/heterophile). It is equal to zero when the mixing in the graph is no different from that obtained through a random assignment of edges that preserves the marginal degree distribution.

Content analysis. The audio transcripts were pre-processed before the content analysis. All transcripts were tokenized, lemmatized, and stemmed. In addition, words with fewer than three characters, stop words and extremely rare/frequent words were also removed. We also performed an N-gram analysis to identify contiguous sequences of *n*-words. Bi-grams and tri-grams revealed key concepts (e.g. global warming and the Paris Agreement) that provided essential information about each livestream. After pre-processing, we used a Latent Dirichlet Allocation (LDA; Blei et al., 2003) model to identify the topics of discussion. The idea behind LDA is that each document (speech) can be described by a distribution of topics and each topic as a set of words. LDA assumes that each document can be represented as a probabilistic distribution of hidden (latent) topics and that topic distribution in a document corpus (all speeches) shares a common Dirichlet prior. The topics defined by the LDA model are clusters of co-occurring words, which may be linked to more meaningful topics under expert analysis. The popularity of the model has dramatically increased since 2003 when the LDA was first presented (Valle et al., 2018; Jelodar et al., 2019; Sharma et al., 2022). For example, Boussalis and Coan (2016) used LDA to evaluate the discourse of climate denials. A similar approach is found in Supran and Oreskes (2021), who analyzed the fossil fuel industry's narrative on climate change.

We used a Python implementation of MALLET's LDA (McCallum, 2002). The number of topics in the model was determined by the coherence score Cv, which is a metric that measures the similarity between the words in a topic. A higher coherence score indicates that the words in a topic are more similar to each other. We tested a range from 1 to 25, and the highest Cv was achieved with 11 topics (0.417), followed by 15 topics. Other model settings included the hyperparameter optimization interval (set to 10) and sampling iterations (1000). Fine tuning ($\lambda = 0.2$) was performed using pyLDAvis tool. Perplexity was used to measure the predictive performance of the model ($P = 378.5$). Results from tests on Cv and P can be found in the supplementary material (SP01 and SP02).

Ideological bias and credibility. We used the Stanford Named Entity Recognition tagger (NER) to extract key information about media sources cited in each stream (Finkel et al., 2005). Transcripts and chat logs were cleaned and tokenized. The list was compared with the Media Bias Fact Check database (MBFC) to evaluate two points: the ideological bias (left-center-right) and the credibility of the source (trusted source-fake news). The MBFC groups source into nine categories, but we merged them into different groups according to these two criteria. As a complement, we also extracted external URLs from the chat files and processed them using the MBFC. A full description of the categories can be found in Table 2.

Context analysis. Twitch has traditionally been considered an informal source of communication and entertainment. However, traditional media and other professional communicators have found an opportunity to increase the audience by using the new platform. The influence of traditional media and journalists drives the inclusion of new formats and content, such as

Table 2 Media Bias Fact Check database grouped into two categories: credibility and political bias.

Credibility	Political bias		
	Left	Center	Right
Trusted sources	left, left-center	center, pro-science	right, right-center
Questionable sources	conspiracy, fake-news (full political spectrum)		

interviews, debates, and science communication, converting Twitch into a more formal source of information.

There are a number of ways to recognize formality in NLP (Pavlick and Tetreault, 2016). Most common analysis include lexical, syntactic, and rhetorical features. Topic analysis is another way to evaluate formality. However, most of these methods are designed for written text and cannot be directly extrapolated to spoken language. For example, contractions are typically indicative of informal language in written text, but not in spoken English. In this context, the use of first-person pronouns may be a better predictor. Conversely, sentence length can be analyzed in both spoken and written text. Censored words are another indicator of informal language, while topic categorization can be used to estimate the degree of formality in video streams (Pamungkas et al., 2023).

We constructed the Context Index (CI) to evaluate the level of formality of each stream. It is based on commonly used NPL tools but adapted to the nature of video streaming. The index ranges from −1 (completely informal) to 1 (completely formal). It is built on four indicators that provide information about the type of content. Three indicators are based on the analysis of the speech: sentence length, formal language, and swearing words. The other is defined by the categorization of each stream. Indicators are weighted according to their importance (see supplementary material for more details). Input data were pre-processed before analysis. This included text cleaning, sentence tokenization (for length analysis), expanded contractions, and word tokenization.

Interactions, attitudes, and sentiment analysis. Being able to stream in real-time while interacting with the audience is one of the most outstanding characteristics of this platform (Gros et al., 2018). On Twitch, viewers can communicate with the streamer or other viewers via chat, thus creating an interactive community. We measured the intensity of these interactions through the analysis of chat logs. For each stream, we obtained a JavaScript Object Notation file (JSON), which was processed to obtain the total number of messages and the count of unique chatters. Before analysis, each file was cleaned up for special characters, URLs, and other non-relevant information, such as ads and promotions included by chatbots.

Viewer's reactions and opinions can be measured by a sentiment analysis tool. In this research, we used the Python API from the Valence Aware Dictionary and sEntiment Reasoner (VADER; Hutto and Gilbert, 2014). VADER is a lexicon and rule-based sentiment analyzer that is specifically trained to identify sentiments in social media. A sentiment lexicon is a lexicon where the words and sentences have been annotated with semantic scores, typically ranging between −1 (negative) and 1 (positive). Every sentence in the text is processed by VADER and the document is then labeled with a sentiment by identifying the most prevalent sentiment. NER and VADER were combined to obtain prevalent sentiments of top-10 named entities.

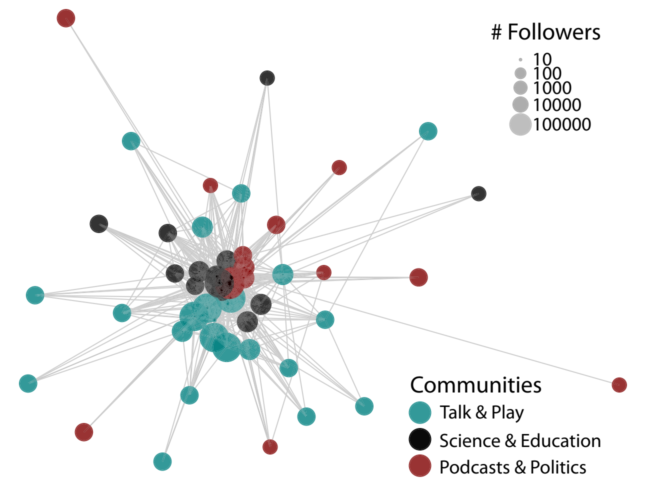

Fig. 2 Undirected network plot constructed on the basis of an adjacency matrix. Each node represents a streamer, with a larger node representing a larger audience (followers); and an edge between two nodes represents a follower shared between the two streamers. Nodes are colored according to their community (bluish-green, black, and dark red). Four isolated nodes were removed for better visualization.

Results

Figure 2 shows the network graph of climate change discussion on Twitch. Nodes are streamers (56−4 isolated = 52 nodes) and edges (557) connect the followers 'shared' between nodes. Node size is defined by the number of followers. The most significant nodes are closer to the center.

Network analysis is crucial for the visual representation of entities that are related to one another. It helps to identify communities, their structure, and their connections with the rest of the system. Our network of interest is divided into three major communities: Talk & Play (TP), Science & Education (SE), and Podcast & Politics (PP). Each community was characterized by the content and the format of the live shows. Streamers in TP broadcast their gameplays while talking about different topics with their viewers. The most influential (followed) streamers were included in this community, as shown in the figure. The SE community comprised science communication and discussion about climate-related topics. The PP category included interviews, debates, and opinions about current affairs, mainly related to politics. The number of streamers was similar in PP and SE (15 and 16, respectively) but slightly larger in TP (21). The most influential streamers in SE and PP were interconnected, which means they shared much of their audience. A moderate modularity score (0.38) may suggest a relationship between communities, in contrast to previous studies on other platforms (Williams et al., 2015; Cann et al., 2021). Connections between communities can be better visualized in the proximity matrix (Table 3; Freelon, 2020).

Table 3 shows the proportion of shared ties between each pair of clusters. While most of the ties in TP are within its own category, it has a close connection with both SE and PP. Another noticeable result is that SE and PP are more interconnected with each other than within their own categories (86 edges compared to 59–76 edges, respectively). These results highlight that followers are transversal to different communities.

One important advantage of Twitch is its ability to carry out synchronous activities (Diwanji et al., 2020). For example, live-stream chats are useful for measuring interactions and the exchange of information between users and streamers. A large number of messages during a live stream indicates an intense social activity not only with the streamer but also between chat

Table 3 Proximity matrix for cross-sectional partition (common edges between communities).

	Talk & Play	Science & Education	Podcast & Politics
Talk & Play	119	116	101
Science & Education	-	59	86
Podcast & Politics	-	-	76
Total edges	557		

users. Figure 3 shows the global impact of 59 livestreams using the total amount of messages and users.

The number of unique users and the total number of messages are closely related. Thus, nearly 20 streams had a very low impact on the community (fewer than 100 comments and fewer than 25 unique chatters). A moderate impact can be found in 32 livestreams, where the audience ranged from 50–100 users and included 300–900 messages. Few cases had a high impact (6 in total) and only one stream had more than 400 unique users and 20,000 comments. The most popular livestreams were political talk shows led by professional streamers.

Users' reactions may also include feelings and emotions. These reactions can be used to define the degree of consensus/controversy of a livestream. One of the things that makes Twitch chat unique, is its use of emotes, which express a feeling faster and more reliably than words can, especially in an environment that provides very little time for others to read your message. For that reason, we included words, sentences, and emotes from chat logs to evaluate users' perception of video streams.

Figure 4 shows tree plots of feelings for the 59 livestreams. Overall, the conversations were dominated by positive and neutral feelings, while negative comments usually remained below 25%. There were some exceptions in which controversial topics and opinions caused a rise in negative comments (e.g. streams 24, 41, and 27). By integrating NER into sentiment analysis, we can identify the emotions expressed about specific entities and achieve a more fine-grained analysis.

Figure 5 shows a double-sided bar chart of the top-10 named entities, along with the sentiment associated with them. *Trump* and *Biden* were the most popular named entities, with an overall positive sentiment. *Congress* and *the Republican Party (GOP)* were the most frequently mentioned named entities in the positive and negative sentiment classes, respectively. *AOC's Green New Deal* and the *Chinese Communist Party (CCP)* had mixed feelings.

Topic analysis provides meaningful insights into the interests of streamers and users. What people are talking about and how they express their ideas is crucial for an accurate representation of the climate change debate. It is worth noting that outputs from objective classifiers, such as LDA, require a qualitative interpretation of results. Therefore, the algorithm computes the optimum number of topics and the selection of keywords for each topic, but the scientist must provide a comprehensive meaning for these. Figure 6 shows the eleven most significant topics found in Twitch.

The selected livestreams covered a wide variety of topics, including climate change discussion, US politics, the economy, and entertainment. Larger circles indicated more important topics. The similarity between topics was represented by how close to one another they appear in the figure. The discussion on the causes and consequences of climate change was the most frequent topic (36% of tokens, T1) followed by discussions on global warming while playing games (11%, T2). US politics were

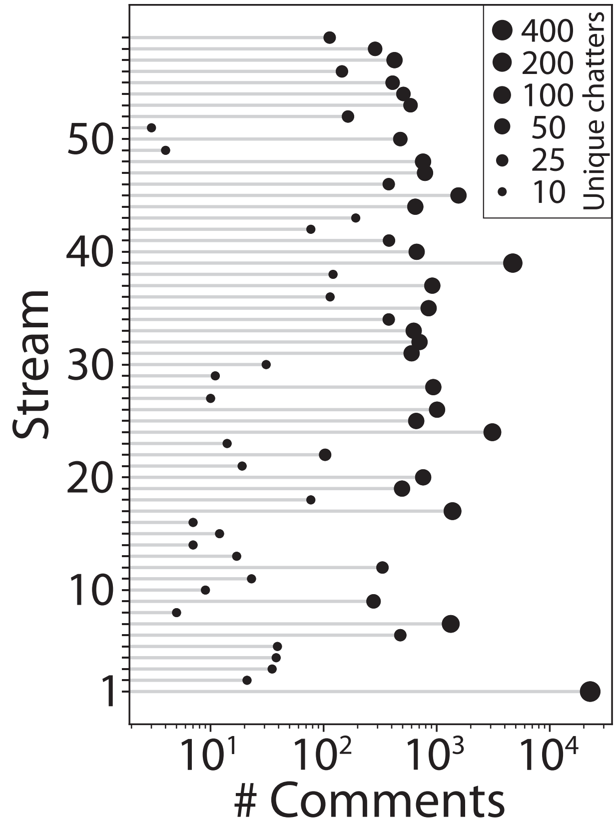

Fig. 3 Stem plot of total messages of the 59 live streams (available chat log). The size of the marker is proportional to the number of unique chat users in each video stream.

also an important topic of debate, especially when Trump was the object of discussion (10% for T3 and T4 and 4% for T9). The prominence of skeptics and deniers was low, with only 3% of tokens. Climate science communication had a moderate impact, with more than 6% of tokens (T6). These results are consistent with those observed in the next figure.

Analyzing media sources referenced in livestreams is another key element deserving attention. It is a useful way to measure ideological bias, fragmentation, and plurality in discussions. We combined the MBFC database with the Stanford NER tagger to identify the sources of information for both the video streaming and the chat log. We obtained results for 31 livestreams, as shown in Fig. 7.

Figure 7 shows that disinformation had a relatively low propagation on livestreams. In fact, more than two-thirds of the data (21 streams) were from trusted sources while 10 videos included a percentage of questionable references. Only in three streams were 100% of the sources questionable. Focusing on ideological bias, we found that most streams were dominated by left-wing and center media sources. Right-wing sources were testimonials (2 streams). Another interesting pattern was that 14 video streams included references from, at least, two different ideological positions. This means there is some degree of diversity in the discourse of the streamer and plurality in the discussion with their audience (videos 4, 11, 13, 19, 23, and 24).

The platform has traditionally been considered a game-related entertainment provider. However, in Twitch, journalists and professional communicators found a novel locus of news consumption for a young audience (Vázquez-Herrero et al. 2022). The CI provides an approximate overview of this point by

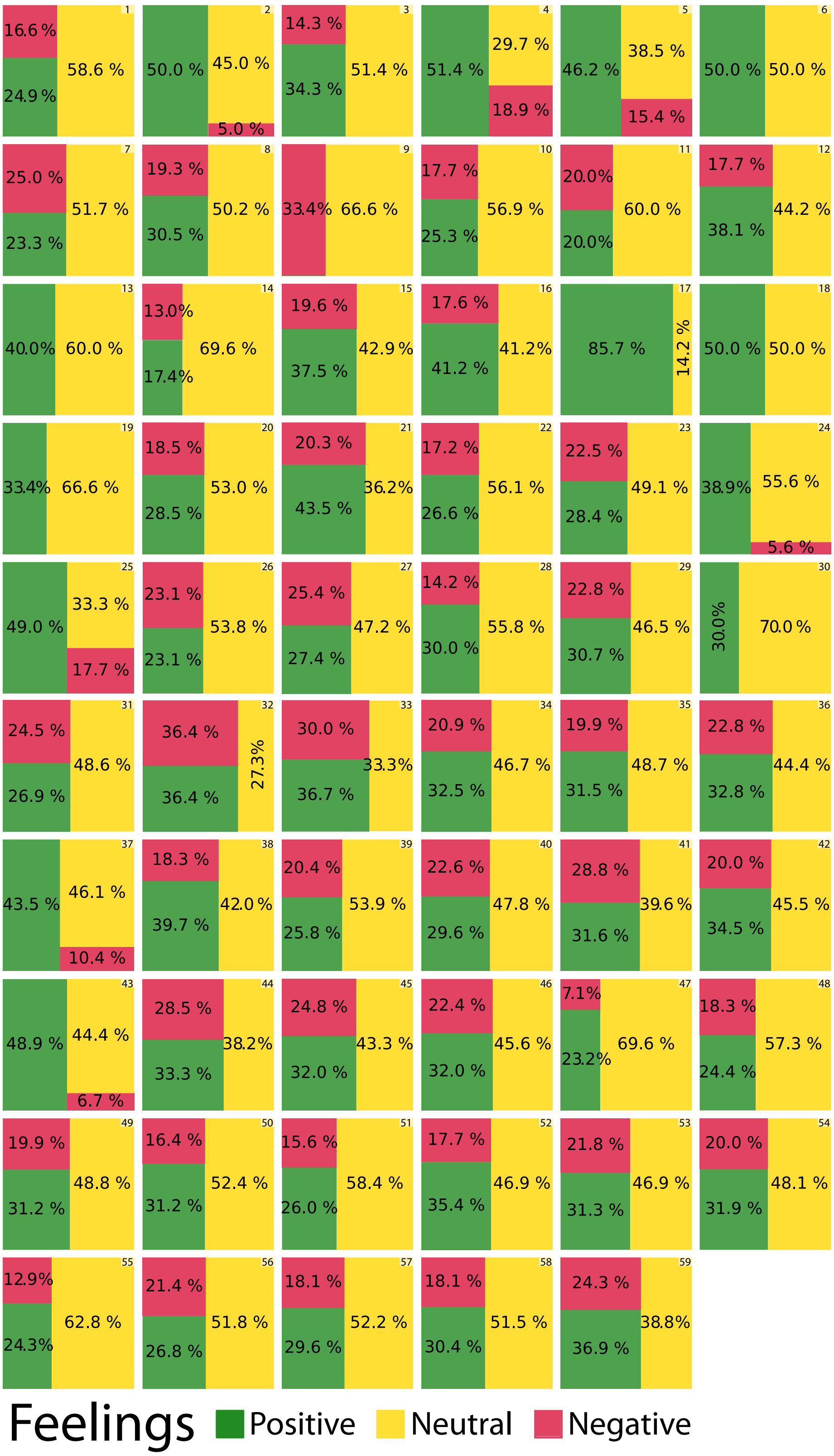

Fig. 4 Panel plot of pie charts of sentiment analysis. Each stream is represented by a square pie chart. Positive sentiments are in green, neutral in yellow, and negative in red. The analysis includes 59 streams.

quantifying the linguistic formality of livestreams. Total views provide a measure of the impact of each stream.

Table 4 shows the level of formality observed in the 78 video streams. Most livestreams were formal and very formal (44.9%), while informal and very informal streams accounted for 39.7%. These results suggest that Twitch is not only for informal chatting but is also a place for formal debates. Nearly 78% of livestreams had a low-to-moderate impact (1–100 views), which means that most streamers had difficulties in establishing a large community of supporters. A small number of streamers were concentrated in the list of most-viewed streams. This situation may have an impact on the construction of climate change discourse.

Discussion

Younger generations have new values, attitudes, and motivations that shape the way they approach the climate change debate. The literature suggests young people are more concerned about protecting the environment than older people (Milfont et al., 2021). This sentiment has become even more salient after the activism of the Fridays for Future movement (Belotti et al., 2022). These changes not only include how younger generations address major societal problems but also the way they keep informed, socialize, and construct their discourse. In this context, new emerging social media can play a key role in the climate change debate, and Twitch.tv seems to include all the ingredients for success.

Twitch is primarily known as a platform for gaming-related content, but other topics have increased in user attention. For example, *Just Chatting* is the most watched category (16% of total viewers) according to twitchtracker.com. Formerly known as *IRL*, this category encapsulates an endless variety of content and has become a place for socializing and promoting discussion and debate. This is what Oldenburg (1999) has described as a 'third place', a physical or virtual space where people can gather to relax, socialize, and engage in civic discourse (Hamilton et al., 2014). Although these 'third places' have been found in other social networks (McArthur and White, 2016; Vaux and Langlais, 2021), Twitch offers additional value by enabling real-time interaction.

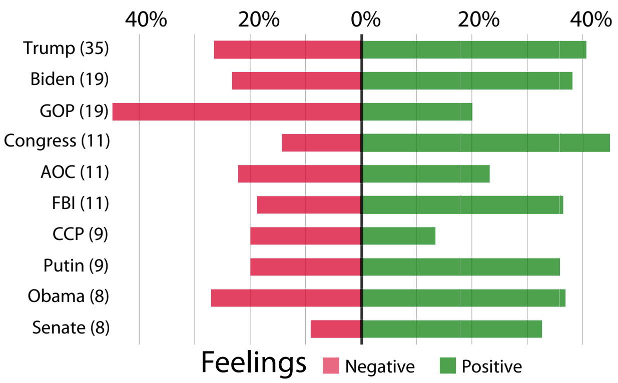

Fig. 5 Double-sided bar chart of top-10 named entities with sentiment analysis. The NER model was used to identify the named entities in the chat, and the VADER model was used to assess the sentiment of each named entity. Positive sentiments are in green and negative in red. The numbers in parentheses represent the total number of chat sentences. GOP Grand Old Party, AOC Alexandria Ocasio-Cortez Green New Deal, FBI Federal Bureau of Investigation, CCP Chinese Communist Party.

Despite the wide variety of topics covered on Twitch, this research revealed that the climate change debate has its own place, as demonstrated by the LDA analysis in Fig. 6. Most livestreams talked about the causes and consequences of climate change, while others focused on the physical basis, the policy design, and the societal response against global warming. A new outcome is that discussion arises in unusual contexts, for example, while playing videogames. This is an informal but frequent way for the twitch audience to exchange opinions. Its importance was confirmed by the network analysis (Fig. 2), where *Talk & Play* included the largest community and most famous streamers.

Another important question is who dominates the climate change discourse. As seen in the results, few livestreams had a high impact on the community (100 views or more). Moreover, these videos were broadcast by only seven streamers. The lack of variety might have an impact on information acquisition and topic discussion. The problem increases when some of these popular streamers use questionable sources of information in their broadcasts. We found that three highly influential streamers included at least one reference to questionable media, and, for one of them, this media was the main source of information (Fig. 7, case 28). The issue here is the potential impact of certain streamers, not the total number of broadcasts including questionable sources, something that we have already shown to be low (10 out of 31 cases). Its impact is also greater due to the large support community, which mostly agrees with the streamer's opinion. For instance, the same case in Fig. 7 (28) had 443 views, 81 unique chatters and only 13% of negative feelings (Fig. 4, case 55). Thus, a few highly influential streamers may contribute to increase the online misinformation on climate change, although this is not the behavior observed in the platform globally.

Regarding interactional polarization—understood as the absence of connections between distinct communities—Fig. 2 reveals meaningful insights. From the network analysis, we understand that the high degree of connectivity between communities is the signal of non-polarized networks (Williams et al., 2015). The assortativity coefficient ($r = -0.28$) and proximity matrix (Table 3) provide quantitative evidence to support this observation. What is more, the most popular streamers in the three communities share audiences, as can be seen from the number of shared nodes in Table 5.

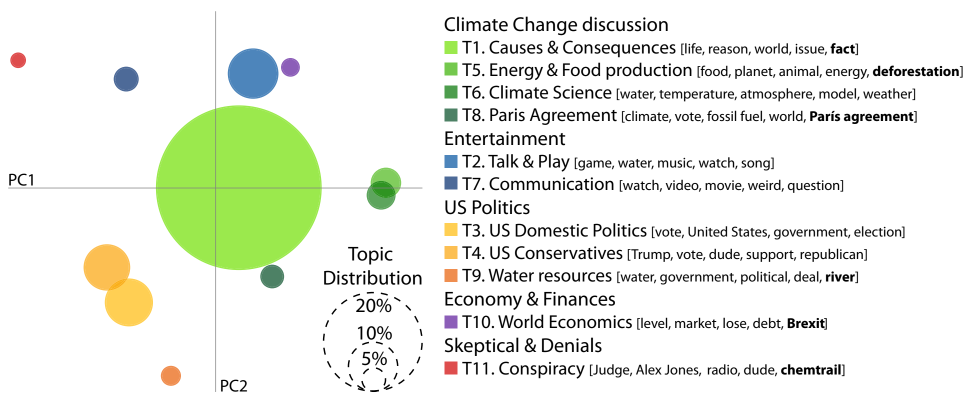

Fig. 6 Topic distribution of the selected streams. For visualization, we decompose 10-dimensional data into 2-dimensions via principal component analysis. The center of each circle represents the position of the topic in the latent feature space while the distance between topics illustrates how dissimilar the topics are. The area of the circles is proportional to how many documents feature each topic.

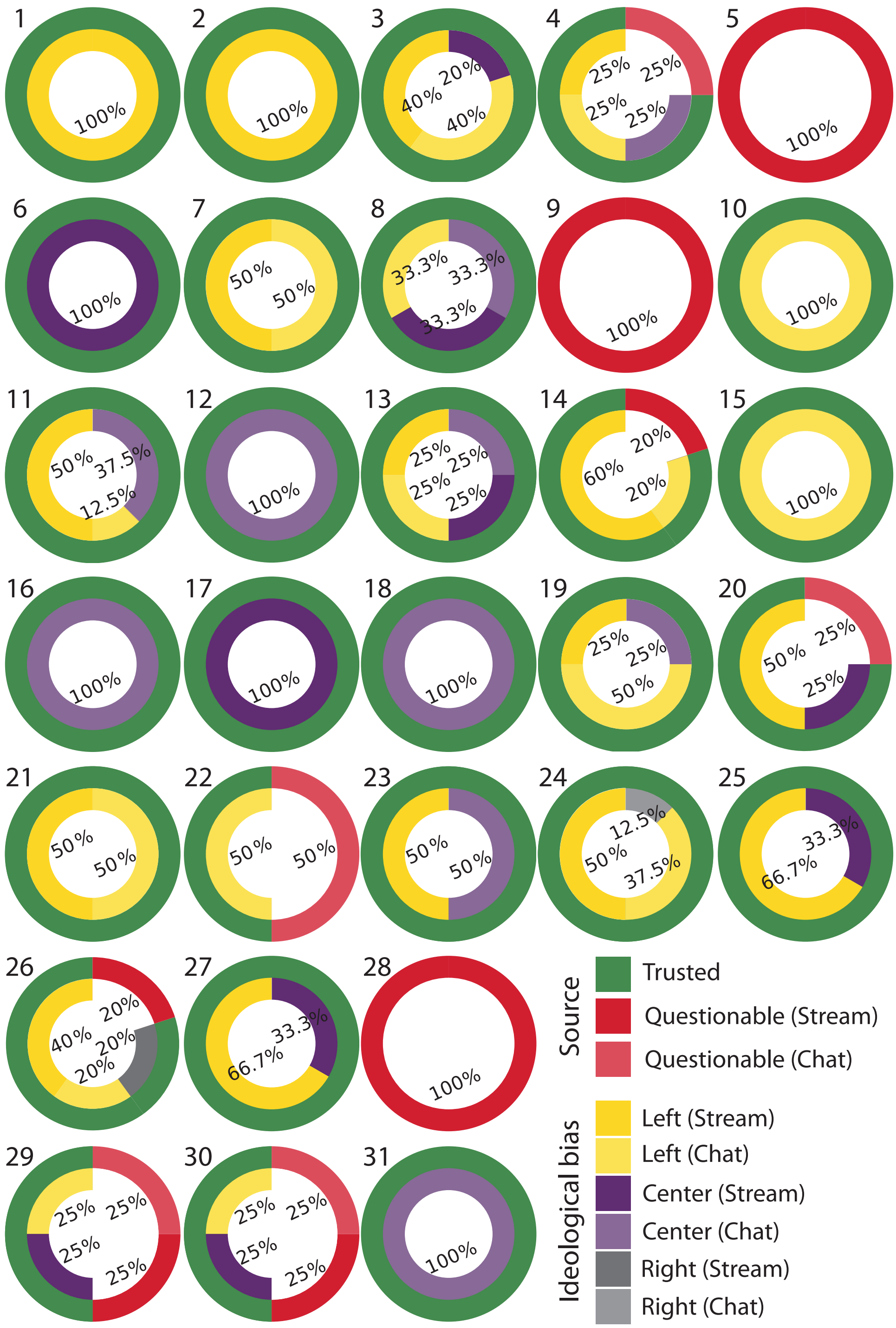

Fig. 7 Double donut charts of sources of information used in 31 livestreams. The outer donut shows the percentage of information that comes from trusted (green) and questionable (dark/pale red) sources. The inner donut shows the ideological bias: Left (dark/pale yellow), center (dark/pale violet), and right (dark/pale gray). Dark colors are sources obtained from the streamer's discourse and pale colors are sources obtained from the chat log. Media sources and categories are based on the MBFC database.

A remarkable feature is that the top 5 streamers on the list are exceptionally well-connected to both internal and external nodes. For example, the two streamers from Podcast & Politics are connected to the 93% of internal nodes and to the 80% of external nodes. Similarly, the streamers from Talk & Play are connected to 95% of internal nodes and to 60% of external nodes. However, the one streamer in the Science & Education category has a weaker internal connection (75%), but a similar percentage of external connections (80%).

The segregation by political preferences, known as positional polarization, is another dimension of polarization on social media (Yarchi et al., 2020). Figure 7 illustrates the political leanings of livestreams based on their source of information. Fourteen livestreams (out of 31) included references from different ideologies and, in nine cases, the audience provided alternative references from another ideological spectrum. These findings differ from other social networks like Twitter, where homophily and echo chambers are common (i.e., greater interaction between like-minded individuals; Cann et al., 2021; Samantray and Pin, 2019). Some authors have argued that shared audiences of different ideologies diminish radicalization, promote tolerance, and facilitate the adoption of intermediate positions (Barberá, 2014; Messing and Westwood, 2014; Wojcieszak, 2010). However, cross-cutting interactions, such as those observed in this study, do not necessarily lead to a deliberative debate. In some cases, it can become a form of trench warfare, where each side is simply trying to score points against the other (Karlsen et al., 2017). From the same figure, we can observe that most references are left- and center-biased, and therefore, more likely to be environmentally aware (Hamilton, 2011; Feldman et al., 2012; Dunlap et al., 2016; Lewis et al., 2019; Marquart-Pyatt et al., 2019). Conversely, right-wing sources are testimonials (cases 24 and 26). These results are consistent with previous research studies where pro-environmentalist attitudes are more prominent in younger generations -the vast majority of the Twitch audience (Johnson and Schwadel, 2019).

A non-polarized network of shared users does not necessarily indicate a lack of a strong community. In fact, Twitch offers a sense of closeness that other platforms do not have. This is because Twitch creates a strong sense of presence and community through its interactive features, such as synchronous chat, co-action, and various other incentives for participation and engagement (Kowert and Daniel, 2021; McMillan and Chavis, 1986). An indirect way to assess the strength of a community is to examine its chats. For example, chat logs can be used to get information about the number of concurrent viewers and then used to estimate the size of each community. In our case, most livestreams have a moderate size of 50–100 chat users, which is ideal for meaningful social interactions that are harder to achieve in large, fast-moving chat rooms (de Wit et al., 2020; Hamilton et al., 2014). The level of participation, the use of positive language, and other metrics such as the percentage of returning viewers can also provide insights into the community's health (Hilvert-Bruce et al., 2018). Figures 3 and 4 suggest that there is a positive engagement between streamers and their audiences, as evidenced by the levels of chat participation and the use of positive language. The percentage of recurrent users is another important metric because it shows that users are interested in the streamer and their content and that they feel like they are part of a community (De Wit et al., 2020). In our sample, we found that the percentage of recurrent viewers ranged from 16% to 21%, which is a respectable figure given the fierce competition. All these data suggest that streamers in this study have built cohesive communities around their channels.

This paper has demonstrated that Twitch.TV can be considered a site for socializing, entertainment, debate, and news consumption. Users keep informed on Twitch not only in an informal context but also by consuming more traditional formats (e.g., interviews). Table 4 highlights that both strategies were quasi-equally distributed: 45% were formal broadcasts and 40% were informal. An increase in these differences is expected because traditional media have found in the platform a new niche to expand their influence among the young audience. This arrival of freelance journalists and news media at Twitch may help to reinforce the rigor and accuracy of the content and, therefore, enrich the debate on climate change. However, traditional media could try to control the information on Twitch (Woodcock and Johnson, 2019). This is something that Twitch needs to prevent by focusing on promoting high-quality content created by amateur streamers. (Johnson and Woodcock, 2019). It should be noted that informal communications do not always imply less rigor or trivialization, as already observed in the results of topic modeling and in the analysis of sources of information.

Table 4 Livestreams distribution according to the Context Index and views (%).

Views	Context Index (CI)					Total (views)
	Very informal	Informal	Neutral	Formal	Very formal	
Low	1.3	7.7	3.8	10.3	5.1	28.2
Moderate	12.8	5.1	9	15.4	7.7	50
High	3.8	7.7	2.6	2.6	3.8	20.5
Very High	-	1.3	-	-	-	1.3
Total (CI)	17.9	21.8	15.4	28.2	16.7	100

Context Index (values range from −1 to 1): Very Informal (≤−0.5); Informal (>−0.5 and ≤−0.1); Neutral (>−0.1 and < 0.1); Formal (≥0.1 and <0.5); Very Formal (≥0.5). Views: Low (1-10); Moderate (11-100); High (101-1000); Very High (>1000).

Conclusions

Twitch.tv is a social media and entertainment video streaming platform where young people stay informed and share their thoughts and beliefs. Livestreaming discussions cover a wide variety of topics, including science, politics, and climate activism. Despite the growing popularity of the platform beyond gaming culture, it is difficult to determine precisely what percentage of Twitch streams are related to climate change discussion, mainly because of the lack of specific metrics and official data but also because of the ephemeral nature of the content. The above reasons and some others make Twitch.tv an underexplored platform for current research on social media. We present a quantitative study that examines climate change discourse on this new emerging platform. Our findings challenge previous results observed for other social networks. For example, behavioral patterns such as homophily and polarized discourse, which are common in Twitter and Facebook, are absent in Twitch. Similarly, the proportion of untrusted sources and fake news remains, for the time being, relatively low when compared with other social media. This is true, at least, in the climate change debate.

This work is novel in three ways, namely, the social network analyzed, the objective methodology applied, and the target

Table 5 List of total ties (internal-external) of the top 5 most popular streamers.

Streamer ID	Followers	Community	Intra-community	Inter-community	Total
35759863	47,000	Podcast & Politics	14 (15)	30	44
78986931	24,331	Podcast & Politics	14 (15)	32	46
26605147	37,280	Talk & Play	20 (21)	22	42
111462736	391,786	Talk & Play	20 (21)	18	38
101238569	10,438	Science & Education	12 (16)	29	41

Intra-community: within-community connections. Inter-community: connections from nodes in other communities. The numbers in parentheses represent the total number of nodes in each community.

audience studied. Despite the advances, there are some limitations that should be considered. The first is the lack of video analysis. Visual content contextualizes streamers' speech and may provide more information about the topic of discussion. However, the core of livestreams is the audio, which is analyzed for the first time in this type of research. The second limitation is the temporal validity of our analysis. This problem is intrinsically linked to the nature of the platform. Twitch.tv is a new, emergent media offering ephemeral content in a state of continual change. The small sample size is another limitation, and as such, the findings of current research should be interpreted with caution. Thus, updates of this work are required to provide an accurate snapshot of the climate change debate.

A finding worth elaborating on in further work by other scientists is that platform architecture and intended commercial goals do not play a decisive role in shaping the topics circulating on them. Indeed, the community has found a way to adapt the platform to its own interests (e.g. The 2019–2020 Hong Kong protests; Ruiz-Bravo et al., 2022). Such stepping outside the framework officially set by the stakeholders is extremely interesting as it shows an emergent property of the system, in the sense that it is the infrastructure, the channel, that is central here, while prior contents and alleged, official uses are secondary. Thus, more analytical effort must be put into the effects of the technology itself than in the actual content addressed in the first place. In other words, what users make of the platform depends more on the technical means it opens up than on the intended orientation given by the owners.

Our work on the communities around the discussion of climate change is an example of how an external, off-topic element can rapidly be brought into the conversation. While we would certainly agree that discussing the climate emergency is a positive thing, there is a downside, in the sense that twitch may provide new and still under-scrutinized avenues for public manipulation, propaganda and dissemination of misleading information. As in traditional media, this dark triad is beyond the control of twitch.tv, but there are new elements here, that is, the target audience, young and still uncritical individuals, and the multiple, polymorphic, and difficult-to-monitor types of content. All of this makes it complex to successfully address potentially damaging issues and set correcting measures. The challenges for parents and educators to control direct, unmonitored, subtle, and almost unrestricted access to the minds of the young generations are daunting.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Received: 31 May 2023; Accepted: 7 November 2023;
Published online: 20 November 2023

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Acknowledgements

The authors acknowledge the financial support of the Spanish Ministerio de Ciencia e Innovación and Agencia Estatal de Investigación, MCIN/AEI/10.13039/501100011033, ERDF A way of making Europe and the European Union NextGenerationEU/PRTR (Projects: PID2022-138298OB-C22; TED2021-131526B-I00; PDC2022-133834-C21). FJT acknowledges the support of the University of Castilla-La Mancha (2022-GRIN-34329). AN also acknowledges the financial support of the Regional Government of Castilla-La Mancha and the European Social Fund Plus (SBPLY/22/180502/000019).

Author contributions

AN: Conceptualization, formal analysis, funding acquisition, investigation, methodology, writing—original draft, writing—review & editing. FJT: Funding acquisition, visualization, writing—original draft. All authors substantially contributed to the article and approved the submitted version.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-023-02377-4.

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