Science by YouTube: an Analysis of YouTube's Recommendations on the Climate Change Issue

Pınar Dündar*, Heritiana Ranaivoson**

* Chief Expert Researcher, TUBITAK Turkish Academic Network and Information Center, Academic Journals (pinar.dundar@tubitak.gov.tr)
** Senior Researcher, imec-SMIT-VUB (hranaivo@vub.be)

Abstract

Citizens increasingly use online platforms, and in particular YouTube, to get informed. This paper addresses the role of YouTube's recommendation system in science communication to assess whether YouTube's recommendation system is creating filter bubbles on the climate change issue. It, therefore, contributes to the growing literature that finds that such filter bubbles actually do not exist. The paper shows that users are likely to get content with similar opinions, at least for a few recommended videos in a row. In addition, it was observed that the same promoters of climate denial appear over and over again in different recommendations. Given all that, YouTube can lead to the creation of filter bubbles where users do not have access to all relevant scientific information.

Keywords: Science communication; YouTube; recommendation system; climate change; filter bubble.

Introduction

Climate change is a global issue concerning every living creature worldwide. There is a scientific consensus around the existence of this climate change, and the risks it carries for human and natural systems. This consensus is led by the Intergovernmental Panel on Climate Change (IPCC), the United Nations body for assessing the climate change scientifically, who provides scientific reports about this topic and determines where there is agreement in the scientific community (IPCC, 2020). Together with IPCC, several scientific authorities and governmental organizations working on climate change issue and provide up-to-date scientific data on this worldwide concern.

However, the scientific consensus on climate change still encounters opposing ideas. Actors with various motivations – and sometimes harmful intentions – use digital media to create and disseminate information disorder, a common form of which is called fake news. Nowadays, it is rather cheap to set up a website or a YouTube channel with videos that look professional, and it tends to be fairly easy to generate an income from the content created by using online ads. Besides, Internet users also have access to tools to actively foster dissemination (such as social media and video-sharing platforms) of their content (Lazer et al., 2018) to theoretically broad audiences all over the world. As a result, in terms of science communication, the public's perception of scientific consensus is threatened and it is even delineated "*as if there is no scientific consensus*" by the climate deniers (Allgaier, 2019, p. 2).

Another type of concern related to science communication on digital platforms is the risk that users get locked in "*filter bubbles"* (Pariser, 2011). Platform users get information in a customized and curated format, notably through the recommendations they get. For example, the search term "proof of climate change" might give different results on Google for an environmental activist and someone with managerial responsibility in an oil company (Pariser, 2011, p. 7). At first glance, getting personalised information might seem like a great advantage and a convenient way of using technology. However, especially when it comes to politics or science, which may affect the population in a broader scale, it can raise new problems if it leads to getting partial, biased, untrustworthy and, simply, false, information.

As the paper develops after, empirical research on the filter bubble usually finds that this concept simply does not prove to be observable. However, as this paper shows, YouTube may be an interesting exception, according to the scarce literature. The aim this study is actually to figure out what the recommendation system of YouTube means from the science communication perspective, and to analyse if YouTube's recommendation system is creating filter bubbles on the climate change issue.

In the remainder, Section 2 discusses how digitization, and especially YouTube, impact science communication. It then highlights potential biases caused by the platform's recommendation system, in particular from the filter bubble perspective. Section 3 describes the methodology used to collect and analyse the recommended videos, grouped in 2 datasets, each composed of 10 paths of 10 videos. Section 4 analyses the results for each dataset, concluding on a comparison of both sets. The last section concludes and discusses the results from the filter bubble perspective.

Literature review

Science communication in the digital era

Davies and Irwin define science communication as "organized actions aiming to communicate scientific knowledge, methodology, processes or practices in settings where non-scientists are a recognized part of the audience" (as cited in Davies and Horst, 2016, p.4). With the increase in scientific specialisation following the emergence of modern science, the information gap between scientists and the public has expanded rapidly. This has led to the need to eliminate that gap between the scientific community and the public, by developing science communication channels between the two groups (Dursun, 2010).

Today, there are many science communication channels including the traditional channels of science journalism, formal or informal education, NGOs, blogs, etc. (Polino & Castelfranchi, 2012), which can be used by scientists. Knowledge-based products can now be made available in a digital format, products can be delivered through the internet, and general services can be searched and found online (Koskinen-Olsson, 2008). The Internet has drastically changed the scale and speed of the way we share and acquire knowledge. Scientists are using the Internet as a medium to share their researches with their peers and with the general public (Gregson et al., 2015). For example, according to a study by Adie and Roe (2013), of approximately 750,000 articles on academic blogs or social networks that were analysed over a year; it has been shown that social media interactions related to academic publications increased by 5 to 10% every month.

Conversely, social media and video-sharing platforms have become one of the main sources of science information for the general public. For example, in their study, De Lara et al. (2017) compared 300 online videos about climate change that are produced to be available only on internet or only on television; their findings showed that the online videos that have been specifically produced to be available on internet were more likely to get people's attention and have more views compared to the other videos that were rather produced to be broadcasted first on TV and later were made available on the internet.

More generally, digital sources of information have a high appeal especially among young people. According to a research included in the Reuters Report, almost half of the population of Generation Y (those aged 25-34) and Generation Z (those aged 18-24) in the US and the UK use their smartphones as the main device from which they get firsthand news mostly from aggregators (Apple News, Flipboard, Upday, etc.), social media or messaging apps (Kalogeropoulos, 2019). That does not mean that these segments of the population do not value traditional news media outlets, they still watch news-breaks on major traditional media outlets (for example the BBC or the Guardian in the UK, and CNN or the New York Times in the US); nonetheless, they rely almost always on digital sources (Kalogeropoulos, 2019). According to a survey by Pew Research Center, 68% of American adults say that they use social media to get news from time to time; Facebook is the most popular internet platform from which they get newsfeed with a rate of four-in-ten Americans, YouTube is the second more common website with a rate of 21%, followed by Twitter at 12% (Shearer & Matsa, 2018).

The digital transition with respect to the spread of information has the potential of creating unprecedented drawbacks on the way information is circulating in regard to fact-checking. For example, Rowlands et al. (2008) found that, contrary to the general belief, the wide accessibility of technology in the lives of those aged 18-24 has not resulted in improving the acquisition of knowledge or developing the skills for evaluating information quality. They characterized the "new form of information seeking behavior" as "being horizontal, bouncing, checking and viewing in nature" (Rowlands et al., 2008, p. 308). In other words, they found that young people (born after 1993) mostly tend to use search engines to get an idea about the content rather than reading thoroughly, and they lack critical and analytical skills to evaluate the information they obtain from the web (Rowlands et al., 2008).

With the digitalization of the information sources, science communication is no longer just one-way from scientific authorities towards the public, but from everyone to everyone. However, it doesn't necessarily mean that we are evolving for sure towards a well-informed society. In this regard, it is crucial to analyse on internet where YouTube stands between the sharing of information and surrounding the users with similar information, which causes 'filter bubble' effect.

YouTube as a science information platform and its recommendation system

YouTube is one of the major Internet platforms in sharing information. YouTube has over two billion logged-in monthly users (almost one-third of all internet users), is used over 100 countries, and can be accessed in 80 different languages. On the 4th of October 2019, YouTube was the second most visited website after Google (Alexa, 2019). On smartphones alone, YouTube reaches more people in the US in the 18-34 age range than any TV network (YouTube, 2020).

Snickars and Vonderau (2009) emphasize the fact that people associate YouTube to a library, an archive, a laboratory or a medium like television. It is also remarkable that more than half (53%) of YouTube users consider YouTube important for helping them understand what is going on in the world, and 19% of them deem YouTube extremely important in respect to making it easier for them to understand the news (Smith et al., 2018).

Like many other online platforms (Netflix, Spotify, Amazon, etc.), YouTube has a recommendation system. This core component of the platform suggests a list of other videos to watch later, while users are on a video page. With, on one side, users, with their different tastes and profiles, and, on the other side, available items; recommendation systems aim at displaying for each user the set of items that is the most likely to maximize the user's utility (Adomavicius and Tuzhilin 2005). Most recommendation systems follow the same steps (Kunaver and Požrl 2017): first they analyse the available information about the user; second, they create a user model which stores the information required by the recommendation process in order to select the most appropriate item(s) for the user; third, they present items to the user; fourth a feedback mechanism enables the recommendation system to track the user's satisfaction with the presented recommendations and adjust the user model accordingly. Recommendation systems rely on an enormous amount of data to generate recommendations (Portugal et al., 2018).

There are three types of filtering in the recommendation systems: collaborative filtering, content-based filtering and hybrid filtering (Adomavicius & Tuzhilin, 2005; Balabanović & Shoham, 1997). Collaborative filtering collects the opinions, ratings, behaviors and preferences of large interconnected communities. When an active user has the same opinions of a group on the quality or relevance of a given content, the algorithm deems that the user is likely to be interested in other contents of interest to the group (Ekstrand et al., 2011; Schafer et al., 2007). In the content-based filtering approach, the system evaluates if the content is similar to the other content that the user consumed before. For example, if you regularly watch videos on YouTube related to a specific topic, it is highly probable that you will be recommended videos about the same topic. Hybrid filtering approach combines the two previous categories by using different hybridization techniques to recommend items (Burke, 2002). According to Maik et al., from 2010 onwards, YouTube has been using a hybrid recommendation approach (as cited in Abbas, 2017, p. 1).

YouTube from the filter bubble perspective

Recommendation systems can come with biases, i.e. imbalance or inequality of coverage on topics (Ranaivoson, 2019). Over the past years, YouTube has been highly criticized for its recommendation system being biased in contributing to create a *filter bubble*. The term popularized by Eli Pariser posits three specific dynamics regarding the way we are recommended content: (Pariser 2011): one is alone in the filter bubble; the filter bubble is invisible; and, one does not choose to enter the bubble. The last point raises autonomy-related concerns (Borgesius et al. 2016).

The filter bubble occurs because the system works in the background and considers all personal experiences such as browsing history, previous queries IP address, social networks, etc. (Bozdag 2013). The term is highly related to the concept of 'echo chamber' which is first used by Sunstein (2007) and can be defined basically as producing and being exposed to a homogeneous content. According to Sunstein (2007), the new technologies including the internet is reinforcing this situation, and causing people to hear echoes of their own voices as such they isolate themselves from others.

The consequences of being surrounded by similar content should be discussed at both personal and social levels. In the sense of being informed on political, moral, or scientific issues in the world, the filter bubble might cause the users never being aware of what others think outside the bubble. "*In a personalised world, important but complex or unpleasant issues (…) are less likely to come to our attention at all*" (Pariser, 2011: 18). The direct consequence of the filter bubble is that every user has access to less diverse content – points of views, ideas, stories, etc. – than what is available, or than what they think they have access to (Ranaivoson, 2019). At social level, the problem is linked to the fact that information is a public good, meaning that each person can benefit from other persons' knowledge. For instance, during a discussion about the climate change issue, where thoughts and opinions are shared, the different parts of the discussion can find a chance to get more information and even enlarge their vision – the so-called "social spreading of information" (Sunstein, 2007, p.44).

A crucial aspect of our research is whether YouTube leads to the creation of filter bubbles. In spite of the fuss around the filter bubble, empirical research proving or infirming its existence is scarce (Hendrickx, 2018). Thus, Haim et al. (2017) note that empirical evidence on the existence of the filter bubble and its effects, especially in the context of news, is limited. In a related way, Borgesius et al. (2016) and Regner (2014) conclude that – in spite of the serious concerns voiced – there is no empirical evidence that warrants any strong worries about filter bubbles, but the debate about them is nonetheless important. Roth et al. (2020) stress that several recent studies show that algorithmic suggestions do not necessarily contribute to the creation of filter bubbles. Of the existing handful of studies, none has been able to prove genuine negative effects of filter bubbles.

To update this literature, we have performed a systematic review of recent literature on filter bubbles in YouTube by searching for keywords 'filter', 'bubble' and 'youtube' on Scopus and Microsoft Academic. Only 7 references were retrieved.[1] The theme and main results are summarized here, while the methodologies are referred to in the next section.

The main point is that almost all these papers are focused on a political approach (in terms of party politics). To test the network for homophily, Kaiser and Rauchfleisch (2020) analyse the channel recommendations on YouTube through the communities related to political channels. It is worth insisting that the study is carried out in the political context through political party and candidate channels and focused only on Germany and the United States. Röchert et al. (2020) investigate the homogeneity of YouTube recommended videos in terms of right-wing populist and politically neutral videos in YouTube. They study 1,663 German political videos and examine the aforementioned two different classes of videos. In his paper where he studies the YouTube recommendation system in detail, Bryant (2020) gives the results of independent tests conducted to replicate the algorithm behind the recommendation system, testing the existence of a tendency towards right-leaning politics video. Regner (2014) studies how personalization algorithms act on YouTube users' experience of the website by distinguishing between two distinct user profiles he created (one far-right and one far-left radical), under identical conditions.

In contrast to the literature on filter bubbles on YouTube, our paper is focused on a science communication perspective. The only other paper with such an approach is Hussein and Juneja (2020) who conduct two sets of audit experiments on YouTube platform on five misinformative topics regarding respectively 9/11, chemtrails, flat earth, moon landing, and vaccine. Their aim is to determine the effect of personalization attributes (age, gender, geolocation and watch history) on the amount of misinformation prevalent in YouTube searches and recommendations.

An interesting result is that all these papers show a tendency to the creation and reinforcement of filter bubbles on YouTube, or on the radicalisation towards far-right content - which stands in contrast to the

[1] Research performed on 2020-12-09, using 'Publish or Perish', without any limitation in time. One reference was removed as it was an opinion piece rather than a research paper.

general literature on filter bubbles as reminded before. Röchert et al. (2020) find that there is a high degree of homogeneity of right-wing populist and neutral political content, in other words, the recommendation network shows a filter bubble effect of the examined videos. According to Bryant (2020), the algorithm shows significant tendency towards right-leaning politics videos, which also include racist views expressed by the alt-right community. This feature of YouTube makes it a strong gatekeeper for the users by pushing them into a loop that reinforces radicalism instead of level-headed factual resources. In a related way, working with a diverse number of seed videos, Roth et al. (2020) show that the landscape of YouTube recommendations tends to be parallel to confinement dynamics. They also find that the most confined recommendation graphs, i.e. potential bubbles, are organized around sets of videos having the highest audience number and a significant viewing time.

In contrast, Hussein and Juneja (2020), after analysing the standpoints and relevance to the search topics of more than 55 thousand of videos, figure out that the personalization attributes do not amplify the misinformation when the users have a brand new account; however, these attributes create an affect once the user develops a watch history. Further analyses also show that a filter bubble effect occur both in the top 5 and up-next recommendations for all topics. Remarkably, for the topic about vaccine controversies, watching videos that promote misinformation direct the users towards more misinformative videos.

Kaiser and Rauchfleisch (2020) and Ragner (2014) find problems somewhat worse for users than the existence of a filter bubble as they conclude on the radicalisation effect of Youtube's recommendation system. Kaiser and Rauchfleisch (2020) show that the algorithm recommends far-right content, including conspiracy theories, white nationalist, or anti-feminist content to people interested in mainstream news. Although Regner (2014) notes that his study does not give a single, conclusive answer; the research shows that YouTube seems to include violent content in the top four recommendations following the seed video. Besides, the study reveals that the content becomes more self-similar as the the users go deeper into the network.

The studies mentioned above show that there is not enough empirical evidence on the concept 'filter bubble' in the literature, and the existing ones are mainly organized around the politics, and not around scientific issues, with the notable exception of Hussein and Juneja (2020). Thus, this research is thought to be a contribution to the literature in terms of discussing 'filter bubble' from the science communication perspective.

Methodology

The principal aim of this research is to find out if YouTube's recommendation system tends to create filter bubbles, with an application to the climate change issue. Within this framework, the behavior of YouTube's recommendation system is analysed in an experimental way based on the videos suggested by YouTube.

The categorization of videos

This study is composed of two stages (described after) at the end of which two datasets were obtained. Each dataset consists in 10 paths of 10 videos each (n=200). Each video was analysed in terms of their content (see Table 1), their number of views. In addition, the video uploaders were classified based on being either a YouTuber (individual channels, forums, student clubs or activist groups) or a professional YouTube channel (TV channels, Non-Governmental Organisations, governmental institutions).

Table 1. The video categorization (Categories 1-4 are based on Allgaier's (2019) typology).

Category	Description of the Category[2]	Short description
1	Videos supporting mainstream science and the scientific consensus view on human induced climate change	Scientific consensus
2	Discussion and debate formats in which mainstream science is discussed with opponents and no particular position is advocated in the video ("journalistic balance")	Debate format
3	Videos propagating denial of scientific mainstream positions, such as denial of human-induced climate change	Climate change denial
4	Conspiracy theories about science and technology without reference to actual scientific discussions	Conspiracy
5	Videos not related to climate change	Unrelated

Source: authors

All numerical information that YouTube provides for each video (such as the number of views and comments) was captured and archived. Building upon Allgaier (2019), five categories have been used to classify all the YouTube videos analysed in both stages. In this study, as in Allgaier's research, the facts provided by the IPCC reports Climate Change 2013 and Climate Change 2014: Synthesis report have been taken as representing the scientific consensus, or mainstream idea, which forms Category 1. Additionally, the videos about alternative energy sources (for example solar engineering researches) were also included in Category 1, even if the main topic was not about climate change. In other words, as long as the videos were somehow related to climate and sustainable energy linked to climate change and if they did not include any debate, nor discussion nor conspiracy theories, they were all placed under Category 1. If the video content was balanced between the mainstream and denial approach, e.g. an interview with people from each side, the video was included in Category 2. If the videos mostly included statements opposing the IPCC position, they were placed under Category 3. If the videos linked the climate change to some conspiracy theories including politicians, climate manipulations, deep state, etc. they were placed under Category 4 (Allgaier, 2019, pp. 7-8).

In addition to Allgaier's four categories, a new Category was added as Category 5, which included all videos that are unrelated to climate change, in other words the videos that are not dealing with climate change. As a result, all the videos were classified under one of the following: "scientific consensus", "debate format", "climate change denial", "conspiracy", and "unrelated" (see Table 1). The Category 5 videos (unrelated) are excluded from the detailed analysis since the main objective of this study is to analyse YouTube's recommendation system and whether it tends to create filter bubbles. This categorization elaborates on previous studies, since Röchert et al (2020) distinguish between two categories (right-wing populist vs neutral political); and Hussein and Juneja (2020) between three standpoints (promoting, neutral, and debunking).

[2] Allgaier (2019, p 7).

The first stage

In the first stage 10 keywords were used, each provided a list of 10 recommended videos:

1. Climate
2. Climate Change
3. Climate Engineering
4. Climate Manipulation
5. Climate Modification
6. Climate Science
7. Geoengineering
8. Global Warming
9. Chemtrails
10. Climate Hacking

The keywords were selected based on Allgaier's study (2019). They are the principal terms about climate change used by the experts supporting scientific consensus, the opponents of mainstream ideas, the engineering expert communities in their technical discussions, and more generally public, policy and media (Allgaier, 2019).

In this study, these keywords were used as initial search terms to figure out what YouTube would be recommending in each step as the user would keep watching the suggested videos and whether the recommendations were creating a filter bubble effect. More precisely, the keyword led a first video. Once this video was watched, a second one was selected and watched among YouTube's video recommendations on the right column on the website. The process was repeated until we obtained 10 videos (per keyword). In the end of the first stage, 100 videos were obtained in total. The collection of the first dataset took place on 19 February 2020.

As the aim of this study is to analyse YouTube's recommendation system on climate change, we did not try to mimick a real user's behaviour and selection process. This stands in contrast to Hussein and Juneja (2020) who consider the effect of personalization attributes. Although users sometimes make choices based on their personal interests, the goal here was to figure out what algorithm provides the user. Therefore, the main rule was to select and click on the first recommended video. Besides, two secondary rules were assigned to the selection process to avoid biases related to YouTube's strategy to keep the user in the same channel or offer advertisement videos.

The first rule consists in the fact that if the content of the first recommended video was unrelated to the topic of climate change and if it was from the same channel as the previous watched video, it would be skipped and the next video from a different channel would be clicked on – even if the next one would be not related to the issue either. The second rule consisted in the fact that if the first recommended video was labeled as advertisement (ad), it would be skipped and the next video would be clicked on – regardless of being related to the climate change issue.

The second stage

To expand our dataset, a complementary approach was applied in the second stage of the study. In this stage, the aim was to figure out what YouTube is recommending when users watch a video that includes climate change denial or conspiracy theory. Therefore, in the second stage, rather than keywords, each search process was started with a video belonging to Category 3 or 4. The videos were chosen based on the AVAAZ report (2020). The aim of this report was to figure out if YouTube is protecting its users from climate misinformation. A series of analysis were carried out in the study of AVAAZ and it is proved that YouTube is causing dissemination of considerable amount of climate misinformation videos to people via its recommendation system, and many popular brands (even some green or ethical ones such as WWF, Greenpeace, etc.) are showing their ads in those misinformation videos (AVAAZ, 2020, pp.10-11).
In the AVAAZ (2020) study, three search terms were selected ("global warming", "climate manipulation", "climate change") and for each term, the 100 most-recommended videos were listed. Each of these videos was analysed, and the appropriate ones were labelled as "climate denial and misinformation videos". In the following part, the researchers listed the top 10 recommended videos for the search term "global warming" and the top 5 most viewed videos for each of the terms "climate manipulation" and "climate change" to investigate which ads were being shown on those videos. Based on this list of 20 videos, and after removing those listed for more than 1 search term, we selected the top 10 most recommended videos to start the YouTube searches. The video titled ACTUAL SCIENTIST: Climate Change is a Scam! was also excluded as it could not be found on YouTube. The 10 climate misinformation videos selected based on AVAAZ (2020, p.53) were:

- What They Haven't Told You about Climate
- The truth about global warming
- Climate Change: What Do Scientists Say?
- Nobel Laureate Smashes the Global Warming Hoax
- CIA Whistleblower Speaks Out About Climate EngineeringVaccination Dangers and 911
- The Great Global Warming Swindle - Full Documentary HD
- WHY I SAID GLOBAL WARMING IS THE BIGGEST FRAUD IN HISTORY -Dan Pena | London Real
- Fatal Flaw In Climate Change Science
- 25 NASA Scientists Question the Sanity of the Global Warmists
- Lord Cristopher Monkton - Global Warming is a hoax

Starting from each of these videos, before and during the searches, the same rules were applied as in the previous stage. The only difference in this stage of the analysis was that the first recommended videos on YouTube were followed by nine (and not ten) videos so as to obtain 10 paths of 10 videos, as the first video was already determined. In the end of this stage, 100 videos were analysed including the 10 ones chosen from AVAAZ (2020). The searches of the videos on YouTube were carried out between 29 March and 02 April 2020.
At the end of the two stages, 200 videos were analysed in total.

Crucially, this paper is interested in the path from one recommended video to another, rather than simply on all videos recommended after having entered a keyword or watched a video. Therefore, it is comparable to Röchert et al. (2020) who consider initial videos and their first and second level recommendations; and to Ragner (2014) who follows the recommended links, maps the different paths, and analyses the videos that the user is exposed to through recommended content, but with the assumption of a radical user profile.

Anonymity settings

We created a new profile on YouTube, to not let our past behaviour on YouTube influence the video recommendations. This way, our identity was concealed so that YouTube would not have previous information about our video consumption. More precisely, the YouTube searches were made using Firefox (Version 72.0.2 (64-bit)). The following adjustments were made to remove personal data as much as possible. In Firefox, under "Settings - Privacy protections" the following selections and arrangements were done:

- Strict
- Do not track: Always
- Cookies and site data always will be cleared (Delete cookies and site data when Firefox is closed)
- History: Never remember history
- Location (Block new requests asking to access your location)
- Camera, Microphone: Blocked
- Block pop-up windows
- Warn you when websites try to install add-ons
- Prevent accessibility services from accessing your browser
- Firefox data collection and use: no longer allowing Mozilla to capture technical and interaction data
- When a server requests your personal certificate: Ask every time
- After each search, always open private browsing

In addition, each search was run in a 'new incognito window'. The videos were watched one by one, the descriptions written under the video together with quotations of the speakers in the video (when relevant) were noted.

Results

The first stage dataset

Among the first stage dataset's 100 videos, the shortest video (*What does the EU Green Deal mean for European Industries?*) lasts 1min 11s, the longest video (*Pumped Dry: The Global Crisis of Vanishing Groundwater | USA TODAY*) lasts 1h 3min 57s.
In terms of video uploader, 8 videos were uploaded by eight different YouTubers and they all support mainstream idea (Category 1). The other 34 videos were all uploaded by 23 different professional YouTube

channels such as DW Documentary, Al Jazeera English, Vox, CNBC, etc. The Category 5 videos are excluded from the analysis.

In terms of video category, 48 videos belong to Category 1 (scientific consensus), only one to Category 2 (debate format), and 51 to Category 5 (unrelated). There is not any video falling neither under Categories 3 (climate change denial) nor 4 (conspiracy). The results can be seen in Table 2.

Table 2. The number of videos and the average number of views per video category for the first stage dataset.

Category	**Description of the Category**	**Number of Videos**	**Average number of views**[3]
1	Scientific consensus	48	667,000
2	Debate format	1	62,748
3	Climate change denial	0	-
4	Conspiracy	0	-
5	Unrelated	51	2,458,552

Source: authors

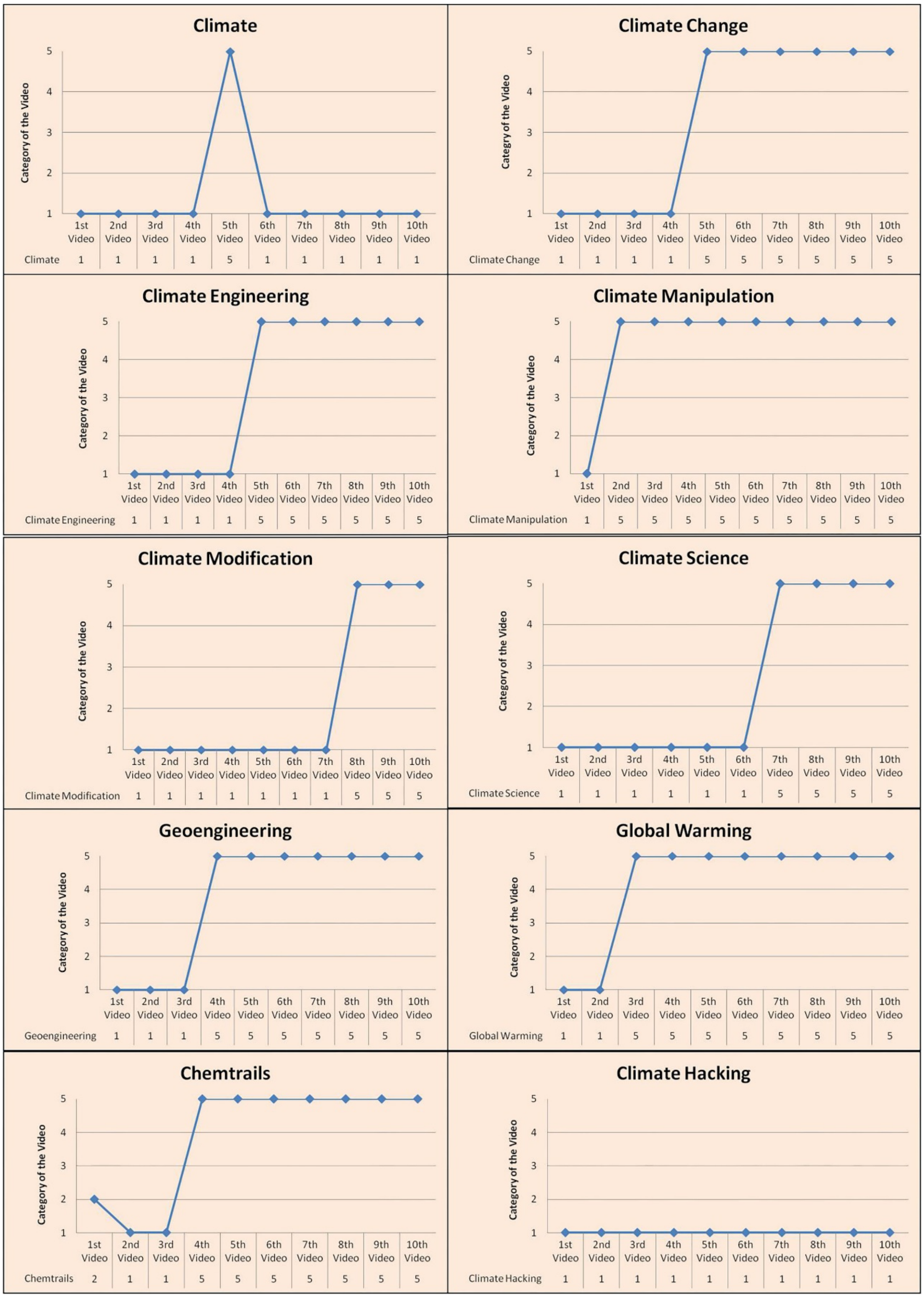
We propose two reasons for the strikingly high number of unrelated videos in the first stage dataset. The first reason may be that once you click on a video that is unrelated, and if that video was composed of different episodes (for example a documentary about alternative energy resources, or arctic ice), it is highly probable that the subsequent episodes are also unrelated to climate change. When the user clicks on the first episode, YouTube automatically recommends the sequel(s) of the video. As each episode is watched in order, depending on how many episodes the video includes, recommendations remain in Category 5.

The second reason why there are that many unrelated videos may be that once the recommendation is off topic; the scope of the starting keyword does not count anymore. In other words, once the user watches a video that is unrelated to climate change, it is unlikely that YouTube will recommend a video about climate change.

The path of the YouTube recommendations for each search keyword can be seen in Figure 1. To understand the graph, we can describe the path for the keyword "climate engineering”. The first video belongs to Category 1, as the second, the third and the fourth. From the fifth until the last video, the recommended videos belong to Category 5.

Figure 1. The overall trends in recommended videos in the first data set based on the categories of the videos. (next page).
Source: the authors

[3] The videos recommended more than once in different searches with different searched keywords are counted only once.



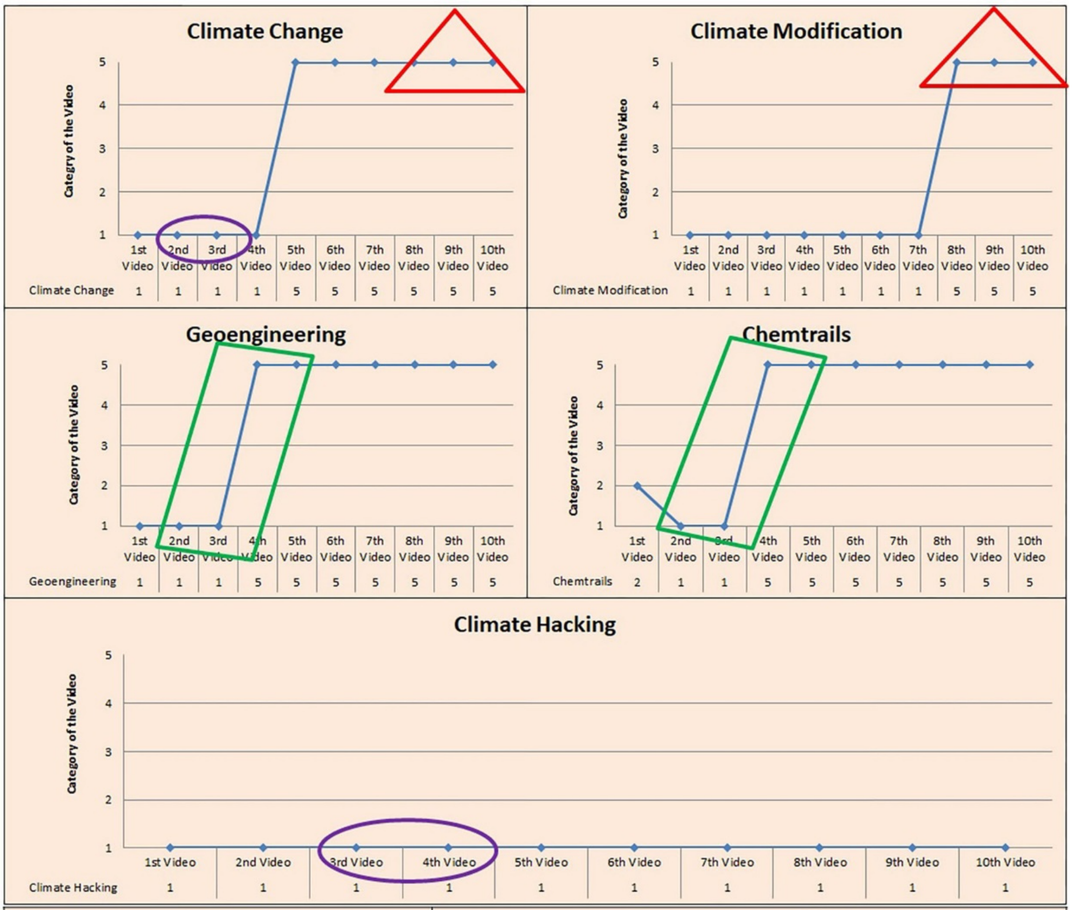
As Figure 1 shows, all first recommended videos support mainstream idea (Category 1). Only for the keyword "chemtrails" the first recommended video is in debate format (Category 2), it is entitled "Chemtrails: Conspiracy Or Fact? | Studio 10". For 8 out of 10 keywords, the user is directed to Category 5 (unrelated) at some point. Only for the keywords "climate" and "climate hacking" the graph starts and ends with

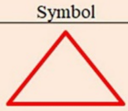
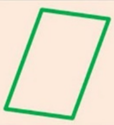
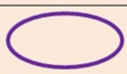
Category 1. As the graphs show, there is no gradual transition between the categories in the overall trend of searches started by different keywords.

We also compare our paths in terms of recurring videos or patterns in the recommendations, i.e. videos and even sequences of videos found in 2 or more paths. 11 videos are recommended more than once by YouTube in searches by different keywords in a total of 87 different videos recommended: 5 Category 1 and 6 Category 5. Videos were uploaded by professional YouTube channels. The videos recommended more than once have an average number of 1,553,092 views.

Furthermore, 3 similar patterns (of 2 or more videos) are observed in the first stage dataset. Figure 2 shows these 3 patterns and the respective keywords' paths they belong to.

Figure 2. The repeating patterns in the first stage dataset. Each different pattern is shown by a different shape with a different color.



Symbol	Pattern of Recommended Videos
	1. National Geographic: Big,Bigger,Biggest: Dam S02E08 2. Mega Ice Breaker 3. Mega Ship
	1. Why Bill Gates Is Funding Solar Geoengineering Research 2. Geoengineering May Be the Answer to Climate Change 3. A.I. Is Making it Easier to Kill (You). Here's How. | NYT 4. Operation InfeKtion: How Russia Perfected the Art of War | NYT Opinion
	1. Melting ice – the future of the Arctic | DW Documentary 2. Climate change: Europe's melting glaciers | DW Documentary

Source: the authors

The second stage dataset

Among the second stage dataset's 100 videos, the shortest video (*Environmentalist rips Ocasio-Cortez, Green New Deal*) lasts 23min 24s, the longest (Patrick Moore - The Power of Truth) 1h 24min 4 s.
In terms of video uploader, all Category 1 videos were uploaded by professional YouTube channels. On the contrary, most Category 3 videos (all except the ones repeated in 2 or more paths, ie 26 out of 29 different videos), and all Category 4 videos were uploaded by YouTubers. The videos that were not uploaded by YouTubers were uploaded by 13 different professional YouTube channels (PBS, Fox News, TedTalks, The Cato Institute, etc.).

In terms of video category, 17 videos belong to Category 1, 52 to Category 3, 3 to Category 4 and 28 to Category 5. No video is classified under Category 2. The results can be seen in Table 3.

Table 3. The classification of the videos in the second data set.

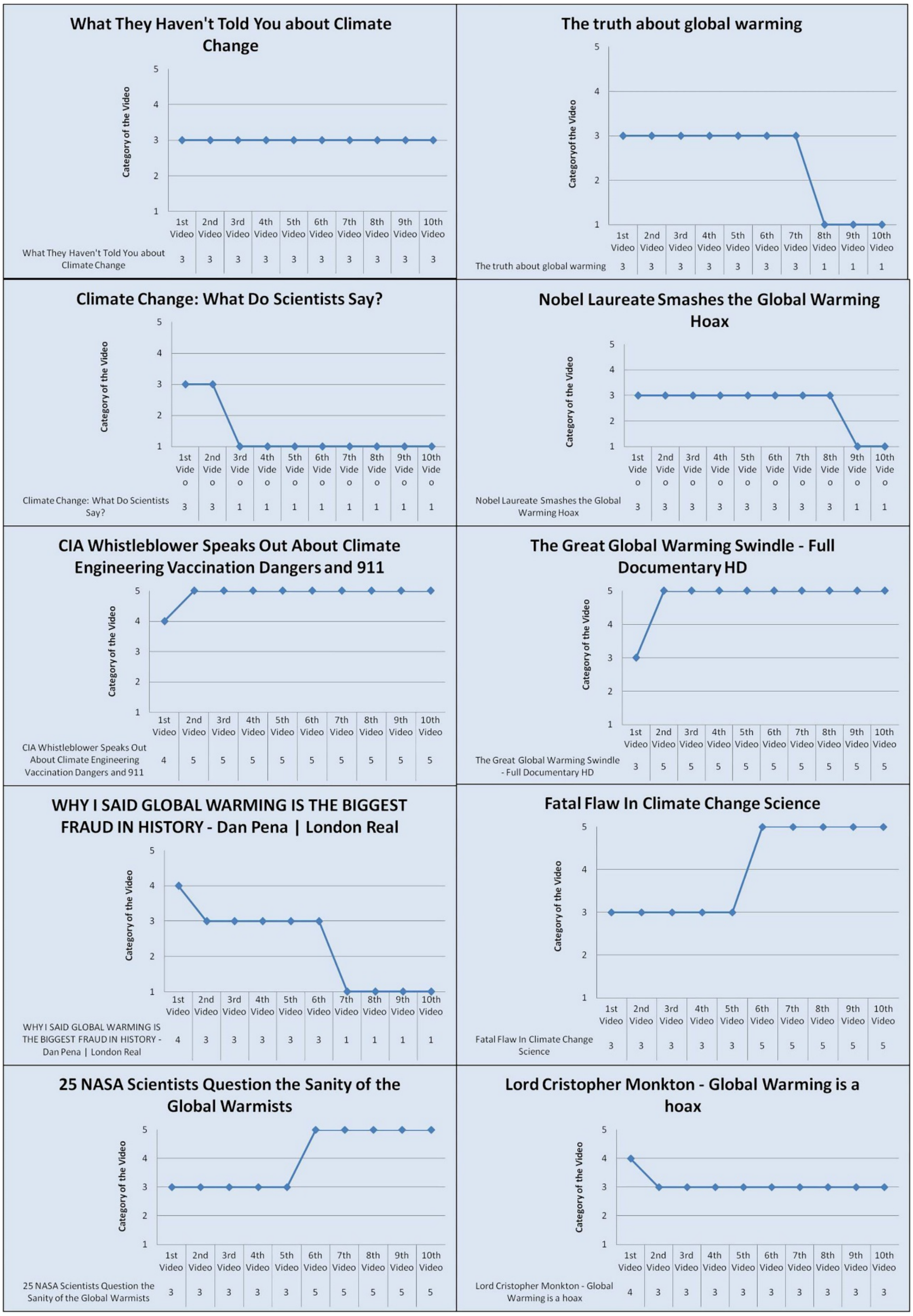
Category	Description of the Category	Number of Videos	Average number of views[4]
1	Scientific consensus	17	882,235
2	Debate format	0	-
3	Climate change denial	52	974,428
4	Conspiracy	3	911,675
5	Unrelated	28	2,536,297

Source: the authors

In terms of average number of views, and excluding the Category 5 videos, 17 different videos have more than 500,000 views, out of which 9 were uploaded by YouTubers. Among these 17 videos, 4 belong to scientific consensus (Category 1), 11 to denial (Category 3), and 2 to conspiracy (Category 4).
Figure 3 describes the paths of recommended videos for each initial video selected from AVAAZ (2020). It shows that only for 4 out of 10 paths, YouTube took the user to Category 1 videos in the end of the path of recommended videos.

Figure 3. The overall trends in recommended videos in the second data set based on the categories of the videos. (next page).
Source: the authors

[4] The videos recommended more than once in different searches with different searched keywords are counted only once.

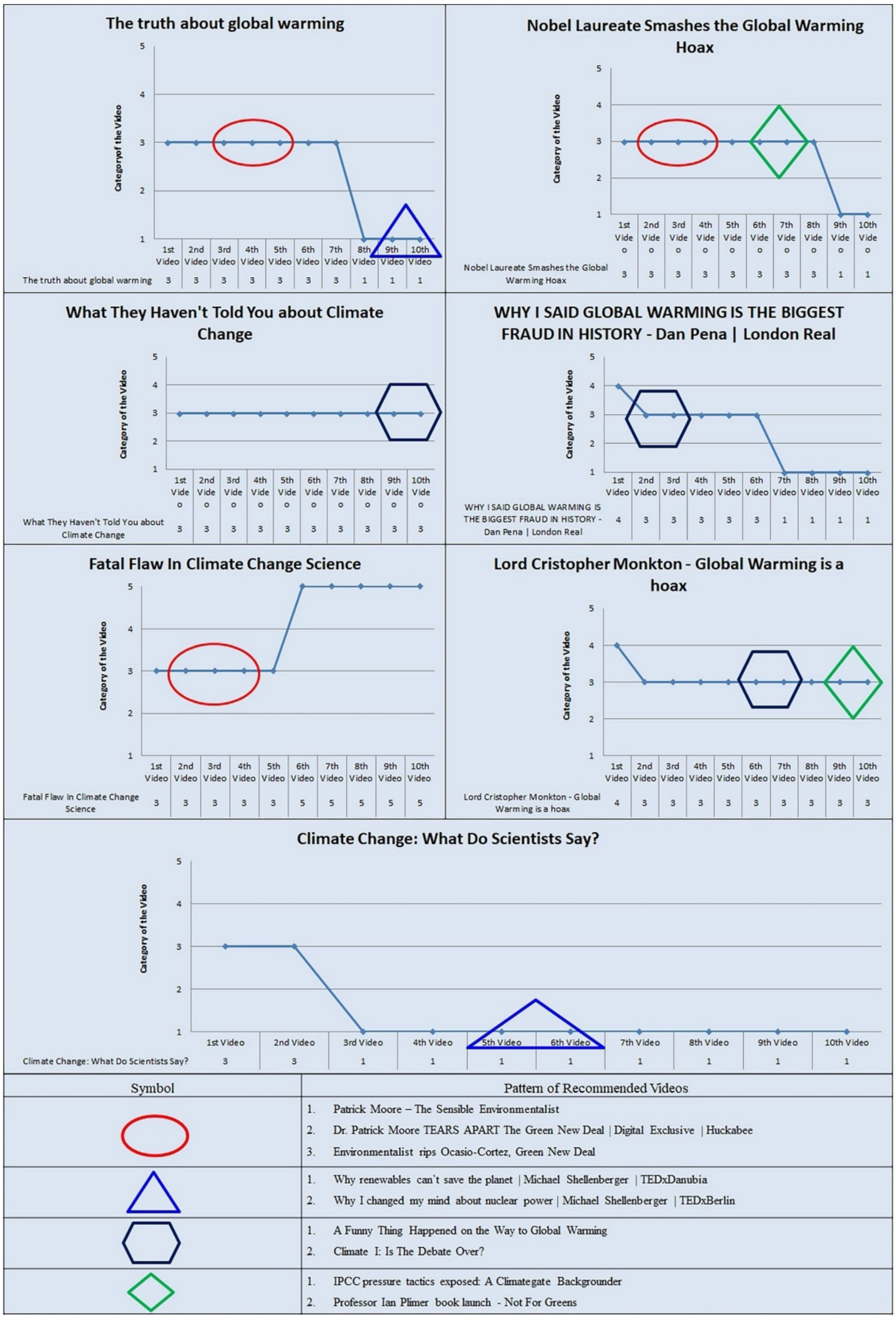


Source: the authors

Like with the first stage data set, we compare our paths in terms of recurring videos and patterns in the recommendations. 15 videos were recommended more than once by YouTube in searches by different keywords, in a total of 72 different videos recommended, with 11 out of these 15 supporting climate denial (Category 3).

Furthermore, 4 similar patterns (same videos in the same order) were observed in the second stage data set as shown below (Figure 4).

Figure 4. The overlapping patterns each of which includes the same videos in the same order. Each different pattern is shown by a circle with different shape with a different color.



Source: the authors

Comparison of the two data sets

The analysis of the first stage dataset first shows that, whichever the search keyword, YouTube is taking the user to videos that are either supporting scientific consensus (Category 1) or unrelated (Category 5). There is almost no recommended video in other categories. The only video in debate format (Category 2), *Chemtrails: Conspiracy Or Fact? | Studio 10*, is recommended as the first video when the keyword 'chemtrails' is written in the search tab of YouTube. However, right after watching this video, YouTube recommends Category 1 videos in the second and third steps, and as from the fourth video, it started recommending Category 5 videos.

In contrast, in the second stage dataset, there is more diversity in terms of category, with no further conspiracy videos during any of the search processes apart from the initial videos from AVAAZ's (2020) lists. However, the abundance of Category 3 videos and the lower number of Category 1 videos show that YouTube kept the user mostly in the same denial category. In the same way, in the second stage dataset, only for 4 paths YouTube took the user to Category 1 videos, and usually this transition took at least 5 videos. For the 6 other paths, YouTube either kept the user in the same category or led them to unrelated videos.

According to the data about which content is uploaded by whom (YouTuber or Professional channel), it is observed that the videos supporting the scientific consensus are mostly uploaded by YouTube professional channels. On the other hand, YouTubers are as effective as professional channels in the dissemination of the information, in terms of the amount of people they reach.

In the first stage data set, among 13 different videos that have more than 500,000 views, there is only one video uploaded by a YouTuber. In the second stage data set, 9 out of 17 different videos having more than 500,000 views are uploaded by a YouTuber. Therefore, the number of views for the videos uploaded by YouTubers shows that individual channels or forums also have a huge impact on science communication, and YouTube can serve as a convenient platform for the dissemination of ideas. This is worrying knowing that the most watched Category 3 and Category 4 videos are the ones uploaded by YouTubers and that there is no Category 1 video uploaded by a YouTuber in the second stage data set.

From the science communication perspective, the high number of views for videos that include 'information disorder' distort the efficiency of the process of getting informed as the number of views of those videos may have a negative impact on the perception of others on the importance of the issue of climate change (Spartz et al., 2015). Although watching a video does not necessarily mean supporting the ideas promoted by this video, a high number of views can be expected to reflect the circulation of these ideas. In other words, the higher the number of views, the more likely the video is shared and causes the dissemination of the idea.

The analysis of both datasets shows that many videos are repeatedly recommended following different search keywords or initial videos watched. On top of it, the user is sometimes directed to watch the same contents following the same pattern. These repetitions cause the users to stay in the same loop and be exposed to the same content.

Furthermore, there is no gradual transition between videos of different categories, as exemplified by the quasi-absence of Category 2 videos. It is therefore clear that for both datasets, the user is likely to be kept in the same category at least for a few recommended videos in a row, which may cause "information blindness", which is a term used by Haim et al. to refer to the filter bubble (2018, p. 330). By feeding users with similar contents, and not helping them broadening their full understanding of the situation, the recommendation system creates a suitable environment for the formation of a 'filter bubble' effect. Even worse, with respect to reinforcing extremist ideas or any kind of 'information disorder', being exposed to same videos may have serious effects in the dissemination of the fake news and the creation of polarization.

Discussion and conclusion

As Nisbet and Scheufele (2009) and (Canfield et al., 2020) stated, to be able to tackle global challenges, scientific information should be communicated in a medium that has a broad spectrum, and YouTube is one of the most convenient medium in that sense. The platform provides an environment open for all and giving voice to everyone, where discussions on science take place with a great potential for dissemination of scientific content. However, its recommendation system is under scrutiny, notably in the academic circles, in terms of its propensity to create filter bubbles. Although the personalised experience is considered beneficial for users and therefore efficient for the platform itself, algorithms suggesting videos to users are highly criticized for running the risk of keeping users in the same perspective and preventing them indirectly from getting access to relevant information, which would lead them to question their own prejudices. There is another potential risk for the users of being exposed to biased information and conspiracy theories.

Although YouTube provides a great opportunity for scientists to tell the story behind their research and reach out to broader audience, it is crucial for users to be critical about the videos they are recommended to consume and be aware of the choices the algorithm makes on our behalf. Using video-sharing-platforms can be challenging, and it may require effort to obtain the trustworthy information. On the other hand, it is not only a problem of the video consumers but also scientists, policy-makers, and ultimately YouTube. The platform provider could decide to revise their algorithms in favor of science communication and contribute to the dissemination of credited knowledge. If the filter bubble is handled by all ends of the YouTube platform, then we can talk about an efficient science communication that may even boost new scientific research and public awareness.

The focus of this paper was to understand YouTube's recommendation system and to find out whether this system is likely to create filter bubbles, with a focus on climate change. The recommendation system can keep citizens in such filter bubbles, preventing them from having access to trustworthy and more diverse information. That can have a huge impact on public understanding of scientific issues such as vaccination, climate change, etc. All that present one of the major challenges that science communication has to tackle. Today, there is a consensus between scientific communities and policymakers on the fact that, if global warming is not dealt with properly, there will be catastrophic consequences for all living forms. On the other hand, there are groups of people who firmly believe that global warming is a hoax and voice that through social media and video-sharing platforms such as YouTube.

This paper has analysed an original set of 200 videos, organized in 20 paths of 10 videos, about climate change. Each video was analysed in terms of content (acknowledging or denying the existence of climate change, or unrelated), of who uploaded it, of average number of views and of their position in their paths (which video led to them being recommended and which video was recommended after they were watched). The analysis shows that the recommendation system of the world's most used video-sharing platform, YouTube, is likely to create filter bubbles and thus plays an indirect role in undermining the efforts of public institutions and scientific authorities in controlling anthropogenic global warming. From the science communication perspective, this situation creates a barrier in promoting critical thinking and opens a rift in the appreciation of scientific developments by the general public.

On the other hand, breaking out of the filter bubble has conflicting results for all users. The filter bubble operates as a barrier between the two camps (climate deniers and the promoters of the scientific consensus) and in knowing what the other camp thinks. Though it is important to have a bridge of communication between the two sides, having an effective control mechanism is crucial to help prevent the reinforcement of the climate deniers' opinions and the spread of information disorder to users especially to those who haven't a clear-cut position on the climate change. Hence, a solution to the filter bubble, while breaking this barrier between the two sides of the aisle, also needs to ensure that citizens are not simply more exposed to denial videos or even conspiracy theories when looking for scientific content. This in order to create a well-functioning discussion environment to engage the two sides in a constructive dialogue.

This paper contributes to a limited literature on filter bubbles on YouTube, in particular as far as science communication is concerned. Based on an original set of data, it shows how YouTube can lead to the creation of filter bubbles in science communication. It is, however, important to highlight the limitations of this work, and hence future research avenues. First, in spite of the anonymity settings, searches were made in Belgium, and in a specific time period (from February to the beginning of April 2020). In other words, the data should not be considered as representative of the usage of YouTube in general and in all countries. The systematic data collection process (watching the first recommended videos, ten times in a row) allows a more direct comparison of (paths of) recommended videos, but they may not reflect users' real behaviours.

Since YouTube is regularly adapting its terms and conditions and its recommendation algorithms, it would be interesting to have the same searches repeated in different time periods and in different countries so to see how the recommendation system is changing over time and getting a better understanding on how YouTube's recommendation mechanism evolves. In addition, an important factor was not included in the study, which are the comments on the video pages that are valuable information showing how a video is perceived by the viewers and how they reacted to the content, thus going beyond the sheer number of views. This can be a subject of future research to study how users react to the video in a scientifically detailed manner. Finally, we believe our framework could valuably be applied to other digital media platforms and to other debated issues such as vaccination, genetically modified organisms, stem-cell research, etc.

Considering the recent researches about Covid19 on YouTube, (Suter et al., 2022; Li HO-Y et al., 2022; Quinn et al., 2022), hot topics in science are already one of the main concerns of scientists studying digital media, and the results are alarming in terms of rising levels of polarization.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Declaration of conflicting interests

The authors declare that there is no conflict of interest.

Bibliographical references

Abbas, S.M., Riaz, M. U., Rauf, A., Khan, M. T. & Khalid, S. (2017). Improved context-aware youtube recommender system with user feedback analysis. *BUJICT Journal*, 10(2), 1–8.

Adie, E., Roe, W. (2013). Altmetric: enriching scholarly content with article-level discussion and metrics. *Learned Publishing*, 26(1), 11–17.

Adomavicius, G., Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the stateof- the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6), 734–749. https://doi.org/10.1109/TKDE.2005.99

Allgaier, J. (2019). Science and Environmental Communication on YouTube: Strategically Distorted Communications in Online Videos on Climate Change and Climate Engineering. *Frontiers in Communication,* 4(36), 1–15. https://doi.org/10.3389/fcomm.2019.00036

AVAAZ (2020, February 12). *Why is YouTube Broadcasting Climate Misinformation to Millions?* AVAAZ. https://secure.avaaz.org/campaign/en/youtube_climate_misinformation/

Balabanović, M., Shoham, Y. (1997). Fab: content-based, collaborative recommendation. *Communications of the ACM,* 40(3), 66–72. https://doi.org/10.1145/245108.245124

Bozdag, E. (2013). Bias in algorithmic filtering and personalization. *Ethics and Information Technology*, 15(3), 209–227. https://doi.org/10.1007/s10676-013-9321-6

Bryant, L. V. (2020). The YouTube algorithm and the alt-right filter bubble. *Open Information Science*, 4(1), 85–90. https://doi.org/10.1515/OPIS-2020-0007

Burke, R. (2002). Hybrid recommender systems: survey and experiments. *User Modeling and User-Adapted Interaction*, 12(4), 331–370. https://doi.org/10.1023/a:1021240730564

Canfield, K. N., Menezes, S., Matsuda, S. B., Moore, A., Mosley Austin, A. N., Dewsbury, B. M., et al. (2020). Science communication demands a critical approach that centers inclusion, equity, and intersectionality. *Frontiers in Communication*, 5 (2). https://doi.org/10.3389/fcomm.2020.00002

Davies, S. R. & Horst, M. (2016). Science Communication. London: Palgrave McMillan.

De Lara, A., García Avilés, J. A. & Revuelta, G. (2017). Online video on climate change: a comparison between television and web formats. *Journal of Science Communication*, 16(1), 1–32. https://doi.org/10.22323/2.16010204

Dursun, Ç. (2010). Dünyada bilim iletişiminin gelişimi ve farklı yaklaşımlar: toplum için bilimden toplumda bilime. [Development of scientific communication in the world and different approaches: from science for society to science in society]. Kurgu Online International Journal of Communication Studies, 2. https://www.academia.edu/3051568/D%C3%BCnyada_ve_T%C3%BCrkiyede_Bilim_%C4%B0leti%C5%9Fiminin_Geli%C5%9Fimi_ve_Farkl%C4%B1_Yakla%C5%9F%C4%B1mlar

Ekstrand, M. D., Riedl, J. T., Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations and Trends in Human-Computer Interaction,* 4(2), 81–173. https://doi.org/10.1561/1100000009

Gregson, J., Brownlee, J.M., Playforth, R., & Bimbe, N. (2015). The future of knowledge sharing in a digital age: exploring impacts and policy implications for development. *IDS Evidence Report*, 125.

Haim, M, Graefe A. & Brosius, H.B. (2018). Burst of the filter bubble? *Digital Journalism*, 6(3), 330–343. https://www.tandfonline.com/doi/full/10.1080/21670811.2017.1338145

Haim, M., Arendt, F., Scherr, S. (2017). Abyss or shelter? On the relevance of web search engines' search results when people google for suicide. *Health Communication*, 32(2), 253–258. https://doi.org/10.1080/10410236.2015.1113484

Hendrickx, J. (2020, February 10). Is de filter bubbel #fakenews? KU Leuven. https://soc.kuleuven.be/fsw/diamond/Jonathan%20Hendrickx%20V3.pdf

Hussein, E., Juneja, P. (2020). Measuring misinformation in video search platforms: an audit study on YouTube. Proceedings of the ACM on Human-Computer Interaction 4, ISSN 25730142. https://doi.org/10.1145/3392854

IPCC (2020, June 20). *The Intergovernmental Panel on Climate Change.* IPCC. https://www.ipcc.ch/

Kaiser, J., Rauchfleisch, A. (2020). Birds of a feather get recommended together: algorithmic homophily in YouTube's channel recommendations in the United States and Germany. *Social Media and Society* 6(4), ISSN 20563051. https://doi.org/10.1177/2056305120969914

Kalogeropoulos, A. (2019, December). *How Younger Generations Consume News Differently*. Reuters Institute Digital News Report 2019. https://reutersinstitute.politics.ox.ac.uk/sites/default/files/inline-files/DNR_2019_FINAL.pdf

Koskinen-Olsson, T. (2008). Access to knowledge in the digital era. *Learned Publishing*, 21(2), 93–102. https://doi.org/10.1087/095315108x288866

Kunaver, M., & Požrl, T. (2017). Diversity in recommender systems – A survey. Knowledge-Based Systems, 123, 154–162. https://doi.org/10.1016/j.knosys.2017.02.009

Li HO-Y., Pastukhova, E., Brandts-Longtin, O., Tan, Marcus G., Kirchhof, Marc G. (2022). YouTube as a source of misinformation on COVID-19 vaccination: a systematic analysis. *BMJ Global Health*; 7:e008334. https://doi.org/10.1136/bmjgh-2021-008334

Nisbet, M. C., Scheufele, D. A. (2009). What's next for science communication? Promising directions and lingering distractions. *American Journal of Botany,* 96 (10), 1767–1778. https://doi.org/10.3732/ajb.0900041

Pariser, E. (2011). *The Filter Bubble: What the Internet is Hiding From You?* New York: The Penguin Press.

Polino, C. & Castelfranchi, Y. (2012). The "communicative turn" in contemporary techno-science: Latin American approaches and global tendencies. In: B. Schiele, M. Claessens, S. Shi (Eds.), *Science Communication in the World: Practices, Theories and Trends*, 3-17. Dordrecht: Springer.

Portugal, I., Alencar, P., & Cowan, D. (2018). The use of machine learning algorithms in recommender systems: a systematic review. *Expert Systems with Applications*, 97: 205–227. https://doi.org/10.1016/j.eswa.2017.12.020

Quinn EK, Fenton S, Ford-Sahibzada CA, Harper A, Marcon AR, Caulfield T, Fazel SS, Peters CE. (2022). COVID-19 and vitamin D misinformation on YouTube: Content Analysis. *JMIR Infodemiology*, 2(1):e32452. https://doi.org/10.2196/32452

Ranaivoson, H. (2019). Online platforms and cultural diversity in the audiovisual sectors: a combined look at concentration and algorithms. In: L. A. Albornoz & Ma. Trinidad García Leiva (Eds.), *audio-visual ındustries and diversity: economics and policies in the digital era*, 100-118. Abingdon: Routledge.

Regner, L. (2014). The YouTube-born terrorist: far-right and far-left radicals' experience of the filter bubble. Journal Exit-Deutschland. Zeitschrift Für Deradikalisierung Und Demokratische Kultur, 2(0), 139–189.

Roth, C., Mazières, A., Menezes, T. (2020). Tubes and bubbles topological confinement of YouTube recommendations. *PLoS ONE,* 15(4), ISSN 19326203. https://doi.org/10.1371/journal.pone.0231703

Rowlands, I., Nicholas, D., Williams, P., Huntington, P., Fieldhouse, M., Gunter, B., ... & Tenopir, C. (2008). The Google generation: the information behaviour of the researcher of the future. *Aslib Proeedings,* 60(4)*,* 290–310.

Röchert, D. Weitzel, M., Ross, B. (2020, July). *The homogeneity of right-wing populist and radical content in YouTube recommendations*. [Conference session]. *International Conference on Social Media and Society (SMSociety '20), Toronto, Canada*. https://doi.org/10.1145/3400806.3400835

Schafer J.B., Frankowski D., Herlocker J., Sen S. (2007). collaborative filtering recommender systems. In P. Brusilovsky, A. Kobsa, W. Nejdl (Eds.), *The Adaptive Web. Lecture Notes in Computer Science*, 4321: 291-324. Berlin: Springer.

Shearer, E., & Matsa, K. E. (2018, September 10). *News Use Across Social Media Platforms 2018*. Pew Research Center. https://www.journalism.org/2018/09/10/news-use-across-social-media-platforms-2018

Smith, A., Toor, S., Van Kessel, P. (2018, November 7). *Many turn to YouTube for children's content, news, how-to lessons.* Pew Research Center. https://www.pewresearch.org/internet/2018/11/07/many-turn-to-youtube-for-childrens-content-news-how-to-lessons/#the-views-and-experiences-of-youtube-users

Snickars, P., Vonderau, P. (Eds.). (2009). *The YouTube Reader*. Stockholm: National Library of Sweden.

Spartz, J. T., Su, L. Y.-F., Griffin, R., Brossard, D., Dunwoody, S. (2015). YouTube, social norms and perceived salience of climate change in the American mind. *Environmental Communication*, 11(1), 1–16. https://doi.org/10.1080/17524032.2015.1047887

Sunstein, C. R. (2007). *#Republic: Divided Democracy in the Age of Social Media*. Princeton: Princeton University Press.

Suter, V., Shahrezaye, M., Meckel, M. (2022) COVID-19 Induced misinformation on YouTube: an analysis of user commentary. *Frontiers in Political Science* 4:849763. https://doi.org/10.3389/fpos.2022.849763

YouTube (2020). *Youtube for Press*. YouTube. https://www.youtube.com/intl/en-GB/about/press/