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*Article*

# Visual Footprint of Separation Through Membrane Distillation on YouTube

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**Abstract:** Social media has revolutionized the dissemination of information, enabling the rapid and widespread sharing of news, concepts, technologies, and ideas. YouTube is one of the most important online video sharing platforms of our time. In this research, we investigate the trace of separation through membrane distillation (MD) on YouTube using statistical methods and natural language processing. The dataset collected on 04.01.2024 included 212 videos with key characteristics such as durations, views, subscribers, number of comments, likes, etc. The results show that the number of videos is not sufficient, but there is an increasing trend, especially since 2019. The high number of channels offering information about MD technology in countries such as the USA, India, and Canada indicates that these countries recognized the practical benefits of this technology, especially in areas such as water treatment, desalination, and industrial applications. This suggests that MD could play a pivotal role in finding solutions to global water challenges. Word cloud analysis showed that terms such as "water", "treatment", "desalination", and "separation" were prominent, indicating that the videos focused mainly on the principles and applications of MD. The sentiment of the comments is mostly positive, and the dominant emotion is neutral, revealing that viewers generally have a positive attitude towards MD. The narrative intensity metric evaluates the information transfer efficiency of the videos and provides a guide for effective content creation strategies. The results of the analyses revealed that social media awareness about MD technology is still not sufficient and that content development and sharing strategies should focus on bringing the technology to a wider audience.

**Keywords:** desalination; emotion analysis; narrative intensity; natural language processing; separation; social media analysis; OpenAI Whisper; water treatment; zero-shot classification

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## 1. Introduction

Nowadays, social media is an integral part of our personal and professional lives [1]. For the majority of people, sharing, liking, and tweeting on social media is a part of their daily routine [2]. Globally, more than 4 billion people utilize social media—approximately 58.4% of the world's population—and users spend 2.5 h every day on social media (January 2022 statistics) [3,4]. As is well known, social media includes web-based tools that facilitate the production and sharing of user-generated content. However, its impact reaches far beyond its simple definition [5]. The widespread use of mobile devices like laptops, smartphones, and tablets has made social media accessible anytime, anywhere. Platforms such as YouTube, LinkedIn, Twitter, WeChat, TikTok, Facebook, and Instagram enable instant communication with millions of people, offering opportunities to connect, share information, and find entertainment, improving the management of daily life [6].

In the modern world, it is more important than ever to understand how to use social media effectively to reach people who are interested in a topic [2]. Educational tools and communication methods have advanced, and social networking has become a key resource for learning. Today, many people turn to social media platforms for educational content, self-training, and effective learning tools [7]. Social media has a particular impact on the dissemination of information [8]. In addition, these platforms have evolved over the last ten years to become the top marketing tools for promotions and will play an even more important role soon [9,10].

Founded on 14 February 2005, YouTube has become the most popular Arts and Entertainment (Streaming and Online TV) website (statistics as of January 2025) [11]. It is worth noting that over one billion hours of video are watched every day and the majority of users are between the ages of 15 and 35 years old; the three genres that are most frequently watched are music, entertainment, and education; English and Spanish are the two most frequently used languages [12]. Visual social media like YouTube offer numerous benefits for learning, including instant access to information, 24/7 availability, collaboration opportunities, storage and sharing capabilities, accessibility, inclusivity, searchability, goal-oriented content, and support for lifelong and self-directed learning. Users can also participate by commenting on, liking, or disliking videos to express their opinions. YouTube reaches a diverse audience, and many educators, researchers, and institutions share educational content on the platform. However, the quality of information on social media is often questionable, and YouTube's lack of content verification can lead to the rapid spread of misinformation [7,13–15].

Data science is a multidisciplinary field of methods, processes, algorithms, and systems for deriving information and knowledge from data [16]. Text mining in data science is the process of extracting patterns and information from textual material [17]. For example, word clouds, a useful tool for extracting important information in text mining, graphically represent the frequency of words in a text corpus [18]. Text mining involves data analysis, natural language processing (NLP), and machine learning (ML) to process large text datasets and identify meaningful patterns. Data analysis refers to the methods used to interpret raw data, generate insights, and improve outcomes while minimizing costs. [19]. The exploratory part of data analysis is crucial to investigate datasets and visualize key properties of the data [20]. Natural language processing approaches enable computers to interact with human text in a number of ways, such as by ingesting text as data, applying this learned knowledge to a variety of text-related activities, and understanding the meaning and correlations between words in the text [21]. NLP has two important subsets: sentiment, and emotion analysis. Sentiment analysis is commonly used to assess an author's attitude or feeling about a certain topic or issue. The emotion analysis task is to assess the user's subjective language for emotional nuances or detect whether the content supports a given point of view [22]. Machine learning (ML) has led significant progress in many fields over the past decade [23]. By identifying patterns from massive datasets, usually in the form of a code, ML aims to predict outcomes [24]. It has three main taxonomies: supervised learning based on labeled data; unsupervised learning based on unlabeled data; and reinforcement learning based on an agent interacting with its environment and modifying its behaviors in response to the received stimuli [25,26]. Numerous application fields, such as healthcare, automatic speech recognition, forecasting, transportation, market analysis, voice analytics, and others, have found widespread use for ML techniques [27,28]. As a supervised task in ML, classification has drawn a lot of interest in a variety of areas and this approach is used to predict group membership for data points [29,30]. Without the requirement for labeled data, zero-shot models, which include zero-shot categorization of text, picture, and other types of data, can perform a variety of tasks [31,32]. Zero-shot classification in text analysis involves labeling text without prior training. It is seeing increasing applications in text mining areas like automated abstract screening, topic, event, emotion, and sentiment classification using zero-shot models [33–35].

Generally, separation with membrane relies on the passage of solvent or solute(s) through a semipermeable membrane that selectively separates some components of interest in a mixture [36]. When a transmembrane driving force (e.g., pressure, temperature, concentration gradient, or electrical potential) is applied, solutes and/or solvents flow through the membrane via different mechanisms, enabling separation and solvent purification [37]. In recent decades, membrane separation systems have been widely used in processes including desalination, water treatment, and wastewater reclamation [38,39]. Depending on the considered separation process, the membrane is commonly formed by a thin porous or dense selective layer prepared on different types of supports [40]. Polymeric, ceramic, metallic, or mixed matrix membranes with nano-additives are commonly used. Selectivity depends on membrane structure, membrane material, and the components of the feed mixture. Polymeric membranes are widely considered in separation systems (e.g., fuel cells, $CO_2$ capture) due to their flexibility, mechanical strength, and ease of production [41–43]. Various types of polymeric membranes have been tailored with specific and amazing structures, forming a flat sheet, hollow fiber, or nanofiber suitable for enhanced separations, including nature-inspired engineered membranes (biomimetic, thermo-responsive, pH-responsive, superhydrophobic and omniphobic, and antifouling membranes, etc.) [44–54]. Furthermore, recent developments in membrane materials have greatly improved separation performance. In general, membrane separation is currently one of the most essential methods considered in the water–energy–environment nexus [55–58]. It is used in the food, desalination, carbon emission control, medical, petroleum, and chemical industries. Furthermore, membrane technology has not only the capabilities of purification, concentration, separation, and refining, but also the features of energy saving and renewable energy generation [43,54,59–70]. Today, membrane separation methods include, among others, pressure-driven separation processes (i.e., microfiltration—MF; ultrafiltration—UF; nanofiltration—NF; reverse osmosis—RO), thermally driven processes (i.e., membrane distillation—MD; thermos-osmosis—TO; membrane crystallization—MCr), electrically driven processes (i.e., electrodialysis—ED; reverse electrodialysis—RED), gas-separation (GS), membrane bioreactor (MBR), forward osmosis (FO), and pervaporation (PV) [19,71]. Each membrane process exhibits advantages and drawbacks depending on the feed solution to be treated and the final objective and use.

MD is a non-isothermal membrane separation technique that is of emerging interest for water treatment, especially desalination, since it combines both thermal and membrane-based advantages [72,73]. In addition to ensure high-quality water recovery and high solute rejection (100% in theory) with its high capacity to retain non-volatile components, MD can be combined with solar energy sources and can be considered for the treatment of hypersaline solutions up to their saturation, making it an environmentally friendly separation technology [74–77]. MD can be operated via four principal configurations: direct contact membrane distillation (DCMD); air gap membrane distillation (AGMD); vacuum membrane distillation (VMD); and sweeping gas membrane distillation (SGMD) [78,79]. Other innovative MD variants have also been proposed with the aim of enhancing the MD separation performance; these include thermostatic sweeping gas membrane distillation (TSGMD); permeate gap membrane distillation (PGMD); liquid gap membrane distillation (LGMD); water gap membrane distillation (WGMD), conductive or material gap membrane distillation (CGMD or MGMD); vacuumed air gap membrane distillation (VAGMD); vacuum multi-effect membrane distillation (V-MEMD); vacuum-enhanced membrane distillation (VEMD); flashed-feed VMD, and sub-atmospheric AGMD [26].

Although MD separation has been explored and examined in many fields, such as recycling discharged RO membrane modules [80,81], reusing wasted MD membranes in MF [82], and determining the global and local themes with artificial intelligence [83], there is still no study revealing the state of MD on any social media platform. YouTube is one of the most visited, vibrant, and dynamic online video-sharing websites on the internet and has billions of users worldwide. This makes YouTube an ideal platform for disseminating technical information on topics like the MD separation process by using its educational and academic potential. There are both professional and amateur content producers on YouTube, and this diversity allows for the exploration of different perspectives and applications of MD. Using video is an ideal tool to visually explain complex MD procedures and laboratory pilot plants. In addition, YouTube's interactivity features, such as comments and likes, provide valuable data to elicit viewers' thoughts and questions about this technology. Therefore, by analyzing MD videos on YouTube, the present study aims to assess the impact, popularity, and commercial potential of MD technology. With the data obtained, the aim is to understand viewers' emotions and expectations and raise awareness of the technology as well by evaluating how MD is promoted on YouTube and its potential industrial implementation. These results indicate how effectively MD is promoted on YouTube and its potential in the water sector.

## 2. Data and Methods

The following keywords were searched on YouTube (www.youtube.com) on 4 January 2024: "membrane distillation", "membrane distillation separation", "direct contact membrane distillation", "air gap membrane distillation", "vacuum enhanced membrane distillation", "vacuum membrane distillation", "sweep gas membrane distillation", "membrane air stripping", "sweeping gas membrane distillation", "thermostatic sweeping gas membrane distillation", "liquid gap membrane distillation", "permeate gap membrane distillation", "water gap membrane distillation", "material gap membrane distillation", "conductive gap membrane distillation", "MD", "MD separation", "DCMD", "AGMD", "VEMD", "VMD", "MAS", "SGMD", "TSGMD", "LGMD", "PGMD", "WGMD", "MGMD", and "CGMD" plus a helper word such as "water", "treatment", "separation", "desalination", or "membrane" to refine the results. These search terms cover key concepts and different applications in the field of MD. The collected videos were first analyzed for titles, descriptions, and tags to confirm their relevance to MD. In the manual video selection, those whose title, tags, description, or content did not match the MD criteria were filtered out, and each author double-checked the filtering process to reduce potential bias in this process. Duplicated videos (identified by transcript similarity through direct observational comparison), even if they had different titles, content creators, or upload dates, were detected and removed from the dataset. The final collection contains 212 data instances (221 with duplicate videos). The dataset has the following characteristics (Table 1).

**Table 1.** Features of the dataset.

| Feature | Data Type | Objective |
|---|---|---|
| Title | Textual | To understand the topic and content of the video quickly. |
| Content Creator | Textual | To evaluate the source and provider of video content. |
| Location | Textual | To identify where more videos are being produced. |
| Broadcast Year | Numerical | To track the trend and evolution over time. |
| Video Duration | Numerical | To understand how much time viewers need to spend watching a video. |
| Number of Views | Numerical | To measure how popular and influential the videos are. |
| Number of Comments | Numerical | To analyze viewers' feedback, questions and thoughts. |
| Number of Subscribers | Numerical | To evaluate how effective and trustworthy the video creator is. |
| Number of Likes | Numerical | To understand how satisfied viewers are. |
| Video Type | Categorical | To determine the format of the video. |
| Video (Transcript) Language | Categorical | To identify the language of the video. |
| Video Transcript | Textual | To analyze the speeches in the video content in text format. |

The basis of selecting these features included understanding the topic and content of the video; evaluating the source of the content; identifying where more videos are being produced; tracking the trends and evolution of videos over time; determining the details, effectiveness, and popularity of the videos; and understanding the feedback, questions, and opinions about the videos. When collecting the dataset, some features of the videos were manually extracted. These features were the title, content creator, year of broadcast, duration, number of views, number of comments (excluding replies), number of subscribers, video type (short or regular video), and number of likes. The transcripts (written record of spoken content of the videos) were downloaded using OpenAI's Whisper architecture (in Python) and the YouTube & Article Summary powered by ChatGPT add-on Chrome extension. Whisper is an automatic speech recognition (speech-to-text) system trained on 680,000 h of multilingual and multitasking supervised data. It is robust to accents, technical jargon, and background noise. It also supports transcription in several languages and translation of those languages into English. The Whisper architecture is a straightforward end-to-end solution that is implemented as an encoder–decoder transformer. The input audio is split into 30 s chunks before being converted into a log-Mel spectrogram and sent into an encoder. A decoder is trained to predict the associated text caption and special tokens are mixed in to guide the single model in executing tasks like language recognition, phrase-level timestamping, multilingual voice transcription, and English speech translation [84]. More information about OpenAI's Whisper can be found in a paper by Radford et al. (2022) [85]. YouTube & Article Summary powered by ChatGPT is a free Chrome extension that allows users to easily view a summary of both YouTube videos and online pages [86]. The language of a video is based on the transcript (i.e., the original language of the video). A word cloud approach was employed for the transcripts. Word clouds are an effective technique for visualizing textual information because they make it simple and fast to identify the key phrases and concepts in a body of writing. Before applying the word cloud method, a preprocessing step was employed to clean up the text (i.e., removing stop words, converting to lowercase, removing accents, removing URLs, tokenization, and lemmatization) with Orange Data Mining Tool (3.37.0). Orange is a free ML and data mining software created by University of Ljubljana (Slovenia) academics Janez Demsar and Blaz Zupan [87,88]. Orange was also used to determine the word counts of the transcripts.

To scrape the comments of videos (excluding replies) the youtube-comment-downloader library in Python (3.9.20). was used. YouTube-comment-downloader is a simple script that can download comments from YouTube without using the YouTube application programming interface (API). The output of this package is in-line delimited JavaScript Object

Notation (JSON) [89]. Emotion analysis and zero-shot sentiment classification were conducted on the comments of the viewers. J. Hartmann's emotion-english-distilroberta-based pretrained model was used to perform the emotion analysis from HuggingFace repository. The model is a DistilRoBERTa-based checkpoint that has been fine-tuned. It classifies data into seven emotions (disgust, neutral, anger, fear, sadness, joy, and surprise) after being trained on six different datasets [22]. The sum of the emotion values of disgust, neutral, anger, fear, sadness, joy, and surprise, which is equal to 1, indicates the relative score of a statement representing an emotion. The zero-shot text sentiment classification was employed with bart-large-mnli architecture of Facebook in Python. The bart-large-mnli model is the checkpoint for the bart-large model, undergoing training on the Multi Natural Language Inference dataset [90]. Three classes (positive, negative, and neutral) were used for sentiment analysis. The relative score of a text belonging to a sentiment is shown by the total of the positive, negative, and neutral values for each review, which was equal to 1.

To compare the data on a common scale, the normalized number of views $(NV_n)$, normalized number of comments $(NC_n)$, and normalized number of likes $(NL_n)$ of a video with respect to the age of the video (in years) were calculated using the following equations (Equations (1)–(3)).

$$NV_n = \frac{NV}{(2024 - BY)} \tag{1}$$

where $NV$ denotes the number of views and $BY$ indicates the broadcast year of the video.

$$NC_n = \frac{NC}{(2024 - BY)} \tag{2}$$

where $NC$ denotes the number of comments of the video.

$$NL_n = \frac{NL}{(2024 - BY)} \tag{3}$$

where $NL$ denotes the number of likes of the video.

The compound annual growth rate (CAGR) was calculated as follows [88]:

$$CAGR\ (\%) = \left( \left( \frac{N_f}{N_i} \right)^{\frac{1}{(Y_f - Y_i)}} - 1 \right) * 100 \tag{4}$$

where $N_f$ is the number of videos of the final year, $N_i$ is the number of videos of the initial year, $Y_f$ is the year the dataset downloaded, and $Y_i$ is the release year of the videos.

The narrative intensity $(NI)$ value of a video was calculated as follows:

$$NI = \frac{WC}{t} \tag{5}$$

where $WC$ is the word count of the transcript of the video and $t$ is the duration of the video.

## 3. Results and Discussions

It is essential to obtain preliminary information before attempting to build a broad framework for the dataset. Figure 1 summarized the outline of the collected dataset.

As can be seen in Figure 1, the collection starts with the first MD-related video entitled "A2 Desalinaters: Water Desalination by Direct Contact Membrane Distillation" in 2011, up to 2024 (2024 not included), with a total of 212 videos (excluding duplicates). The first article on MD was published in 1967 [91], while YouTube was founded in 2005. When these two criteria are brought together, it is obvious that MD is not adequately represented on this visual social media platform. Other parameters that prove this poor representation are the total duration of the videos and the total number of audience interactions (comments, views, subscribers and likes). A video on average lasts 22 min 48 s, receives ~1 comment, has ~1791 views, receives ~21 likes, and the mean number of channel subscribers is ~9912 (note that not all the channels stream only information about MD). If we divide these values by the average video age (~4 years), the results do not look good in terms of MD. In Figure 1, the only optimistic data relate to the compound annual growth rate. The number of MD videos uploaded to YouTube is increasing by 36.48% (note that the compound annual growth rate was calculated between 2011 and 2024). Considering all the above data, we invite the MD community to make further efforts to promote their studies related to MD to a wider audience via YouTube. YouTube content producers who disseminate MD information include a broad spectrum of private and legal entities, such as non-profit organizations, universities/research centers, companies, individual users, conference organizers/event management companies, professors/lecturers, and students. Other highlights of the collection are as follows: the longest video, with a duration of 1 h 57 min 29 s, entitled "Brine Resource Recovery Workshop-Part 1/2" was uploaded in 2023 by "Circular Economy for Climate and Environment (CECE)" [92]; the shortest video of only 6 s, entitled "Membranes-Membrane Distillation", was released by the "Visual Encyclopedia of Chemical Engineering Equipment-University of Michigan" [93]. The most viewed (148,000), commented on (54), and liked (1400) video is "Freshwater from salt water using only solar energy", streamed by "Rice University" [94].

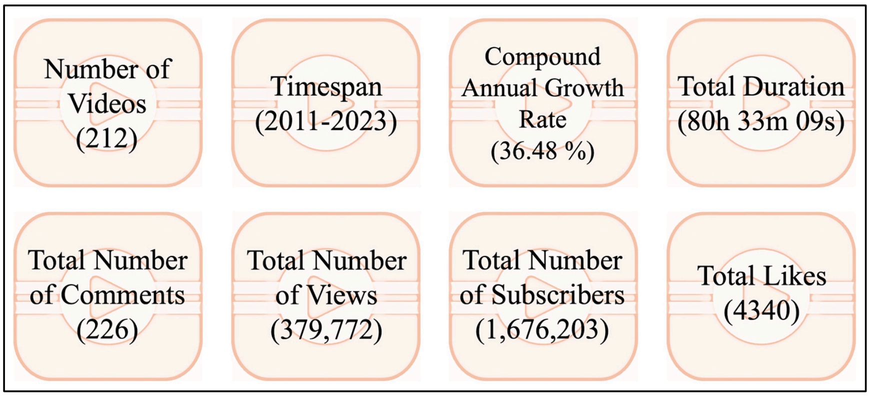


**Figure 1.** Overall features of the collected MD video dataset.

The following figure (Figure 2) shows the MD videos uploaded to YouTube annually. As can be seen, the number of MD videos uploaded is not sufficient, but there is an increasing trend, especially since 2019.

By the end of 2023, the number of MD-related videos on YouTube reached 57, and in the coming years we hope that scientists working in MD will not limit their work only to the laboratory but will also consider the transfer of information on social media platforms. It has been proven that 2012 was the year that MD started to gain much importance [19]. The number of MD studies has expanded significantly since that year. Remarkably, this increase coincided with the years in which videos related to MD began to be uploaded to YouTube. This parallelism highlights the importance of social media sharing of MD and points to the need to adopt more comprehensive and strategic approaches for the future. MD researchers should therefore use social media channels effectively to raise public awareness, facilitate access to information, and disseminate their research results to a wider audience.

To understand the viewer interaction statistics of videos (i.e., the number of views, likes, comments, and subscribers) and to uncover underlying relationships, a scatter plot matrix (pair plot) approach is used, and the results can be seen in Figure 3. In the matrix, the lower triangle shows the distribution between pairs of variables with scatter plots, the upper triangle shows the correlation coefficients between pairs of variables, and diagonal cells between these two triangles show the distribution of each variable with histograms.

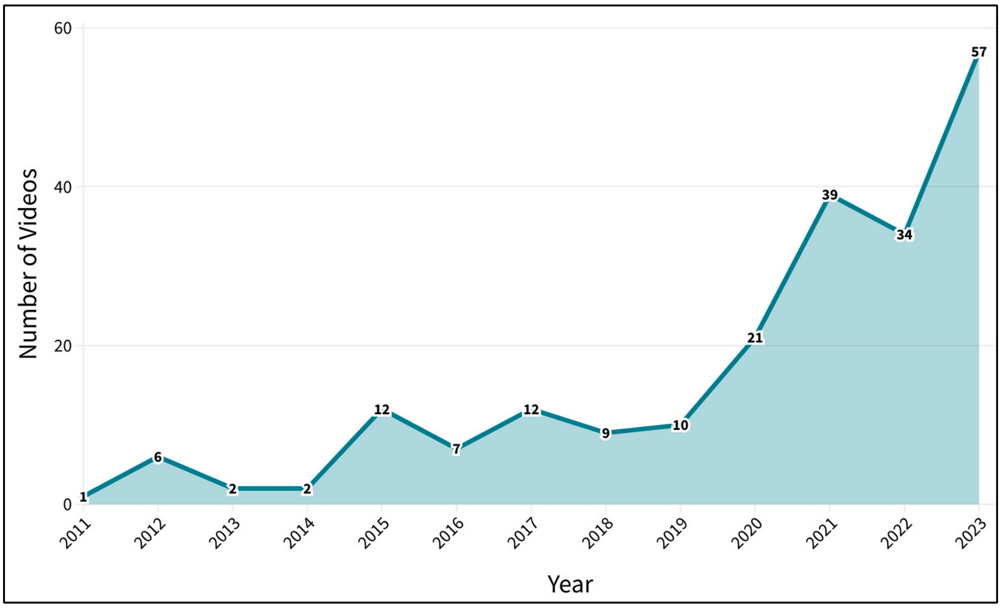


**Figure 2.** Number of MD videos uploaded to YouTube annually.

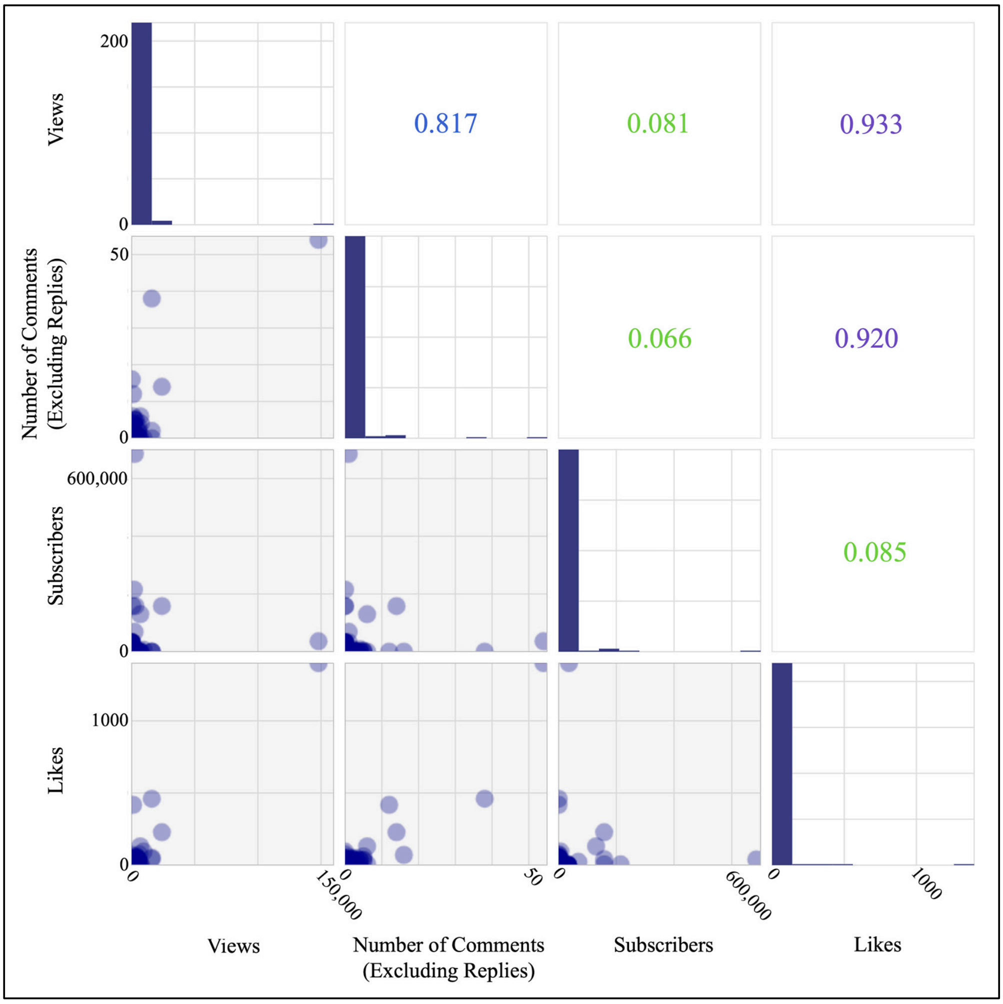


**Figure 3.** Pair plot of number of views, likes, comments, subscribers of the MD videos.

The histograms (diagonal cells) in Figure 3 confirm that all viewer interactions (i.e., the number of views, likes, comments, and subscribers) are low for most of the MD videos. Nevertheless, a small number of videos achieve very high numbers of views, subscribers, and likes. These results indicate a skewed distribution in the viewers' interactions with the videos. Interpreting the scatter plots (lower triangle) and correlation coefficient values (upper triangle) together in Figure 3 allows us to better understand the relationship between variable pairs. The views vs. number of comments scatter plot shows that videos with a high number of views usually have a high number of comments. Also, the correlation value of these two variables is 0.817, which proves that there is a positive correlation and the relationship between the variables is high. The views vs. subscribers' scatter plot shows that videos with high view counts usually have high subscriber counts. However, some channels with a high number of subscribers also have videos with a low number of views, which indicates that not all videos of a channel with high subscribers are always highly viewed. The correlation value of these two variables is 0.081, which means that the number of subscribers has little impact on the views. The views vs. likes scatter plot shows that there is a general positive correlation between the number of views and the number of likes. Videos with a lot of views generally also have a lot of likes. The correlation coefficient of 0.933 points out that the relationship between the variables is high and positive. The number of comments vs. subscribers' scatter plot does not indicate an overall relationship between these variables. The correlation value, calculated as 0.066, also shows that there is a weak relationship. Having more subscribers is not necessarily associated with a high number of comments on MD videos. The number of comments vs. likes scatter plot shows that there is an overall positive relationship between these two variables, meaning that MD videos with more likes generally receive more comments. The correlation value of 0.920 further confirms this relationship. When analyzing the scatter plot of subscribers vs. likes, it is difficult to talk about any relationship. The correlation value of 0.085 already shows that there is a weak relationship between the variables. In other words, the number of subscribers of channels containing MD videos has little effect on the number of likes.

This study further examined the distribution of the video type, transcript language, uploader, and comment language to provide important insights. The results are plotted in Figure 4.

English is the world's lingua franca, so creating content in English is the most effective way to reach a wider audience. The first inference that can be drawn from Figure 4 is that English is the dominant language used in videos (157) and comments (197), allowing content creators and viewers to connect with people from different cultures and backgrounds, and thus expand their reach and influence. The reason for the broadcast and comments in Arabic and Indonesian is that the related countries devote great importance to the issue of obtaining drinking water from seawater, including MD desalination. Content creators should recognize the importance of producing videos in local languages of water-stressed regions to effectively disseminate information about MD technology. Given MD's potential role in addressing the global water crisis, engaging with local communities in their native languages is crucial to ensure the technology's adoption and impact in the future. Most MD-related videos are normal YouTube videos (206) and only 6 are shorts, which are brief, vertical videos that last no more than 60 s. The dominant content creators (>1 video) are illustrated in Figure 5.

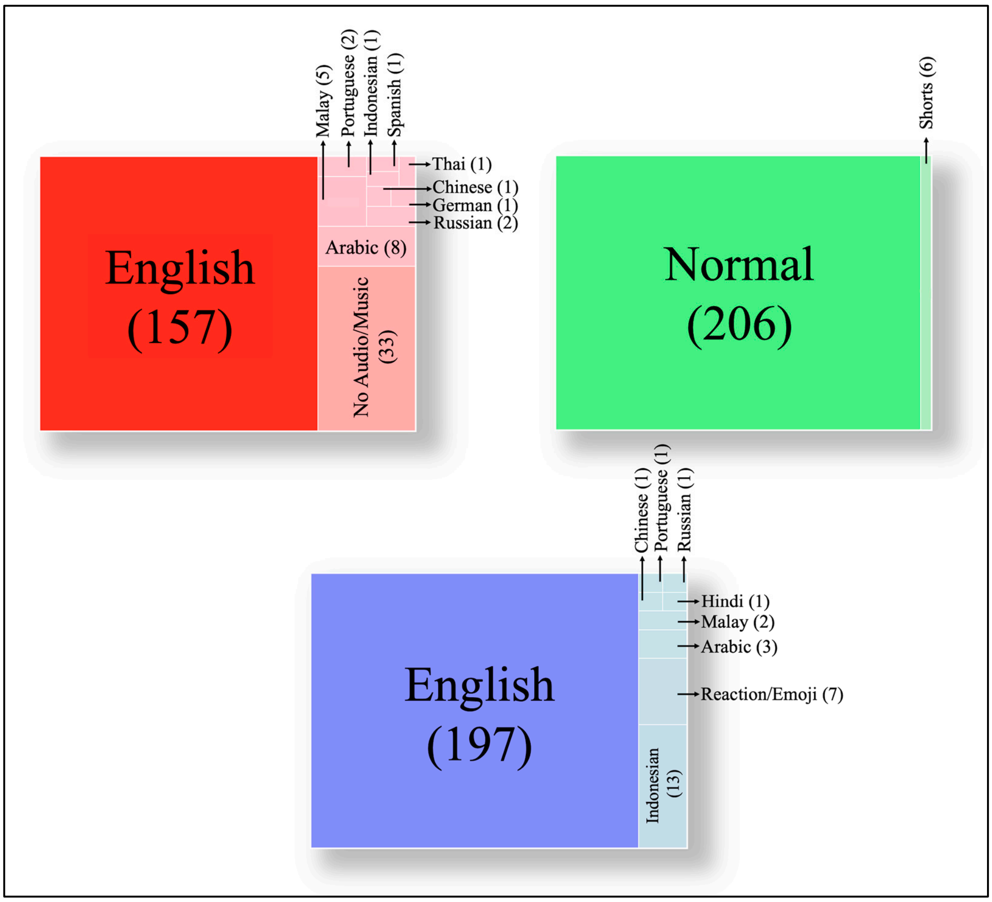


**Figure 4.** Distributions of video language (reds), video type (greens), and comment language (blues) of the MD videos.

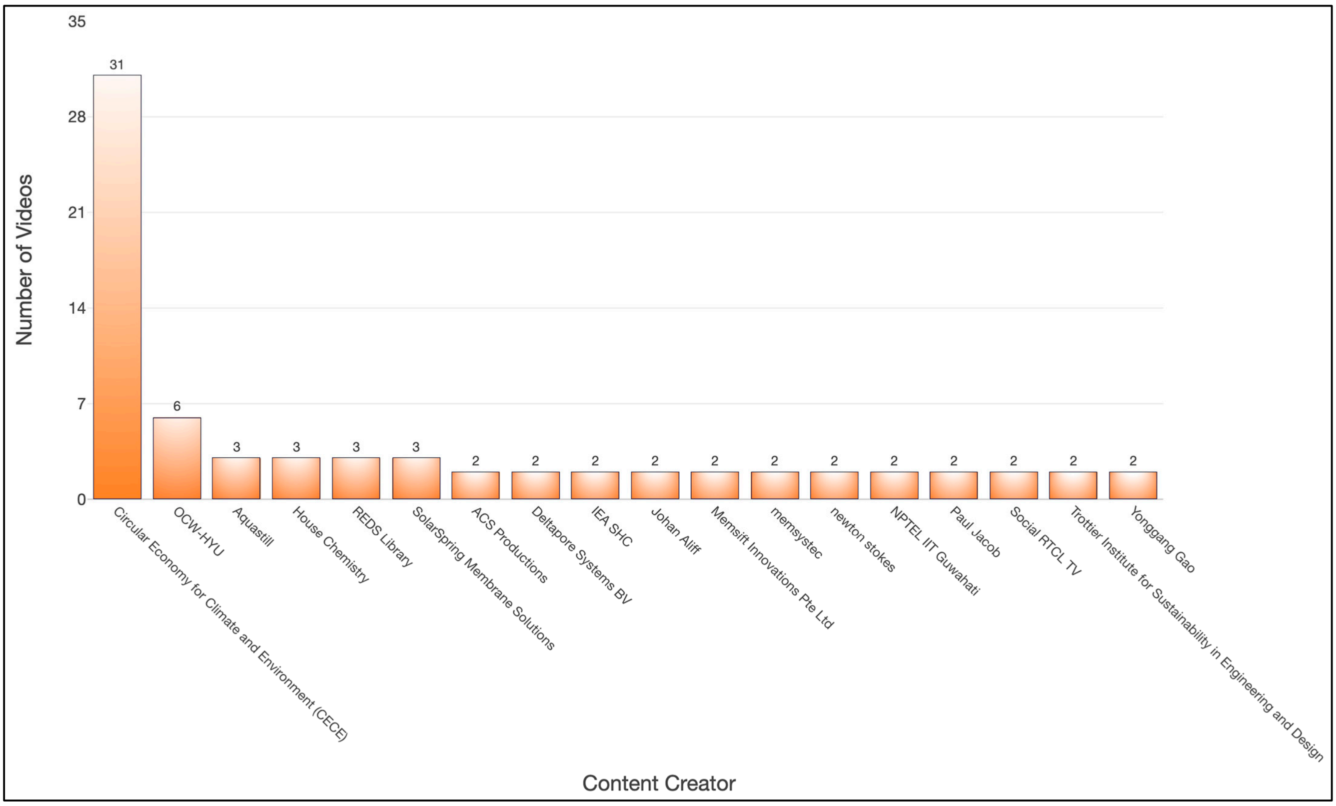


**Figure 5.** Top content creators who uploaded the most MD-related videos on YouTube.

There are 157 content creators who mentioned MD on their channels, but among them, 139 only uploaded a single MD video and only 18 content producers have more than one video on YouTube about MD. This indicates that there are very few channels that continuously broadcast about MD. As can be seen in Figure 4, the channel that produces the most content on MD is "Circular Economy for Climate and Environment (CECE)", with 31 related videos. From 2020 onwards, this content producers' vision has been to achieve a circular economy for food, water, climate change, waste, a cleaner environment, and to inform society by publishing videos from valuable scientists and managers on different topics. The content creator with the second-highest number of MD videos is "OCW-HYU" (six videos). This is Hanyang University's channel, which was formed in 2008, and aims to broadcast the course content of its faculty members. Apart from these two channels, the content creators with the most videos on this topic are membrane/water treatment companies promoting their wastewater treatment products and solutions on YouTube.

Viewer engagement with a YouTube video is a topic that needs to be looked at in more detail. If a video has many views, it means that the video is interesting, entertaining, or informative. In addition, factors such as promotion and sharing, the title and description of the video, the popularity of the video owner's channel, tags, search words, and the thumbnail can also affect the number of views. YouTube comments are where viewers express their opinions, thoughts, ideas, and views regarding the video's content. Comments show whether viewers like or dislike the video, which parts are fascinating, and which areas need further explanation. Comments also serve as a forum for viewers to communicate, discuss, and debate with each other. Subscribing to a YouTube channel allows the user to receive notifications about new videos from that channel and ensures that videos are displayed on the user's homepage or in email alerts when they are uploaded. The likes for a video on YouTube demonstrate that users enjoy the video's content. By clicking the like button, users provide positive feedback to the video's owner and demonstrate the video's quality to other viewers. The most popular videos according to different aspects of viewer interaction (e.g., views, comments, likes, and subscribers together with their normalized values) are given in Table 2.

**Table 2.** Top viewer-interacted MD videos.

| Category | Value | Upload Year | Title | Content Creator | URL |
|---|---|---|---|---|---|
| Views | 14,800 | 2018 | Freshwater from salt water using only solar energy | Rice University | https://www.youtube.com/watch?v=z36jMKk-AdQ (accessed on 4 January 2024) |
| Normalized Views | 24,667 | 2018 | Freshwater from salt water using only solar energy | Rice University | https://www.youtube.com/watch?v=z36jMKk-AdQ (accessed on 4 January 2024) |
| Comments | 54 | 2018 | Freshwater from salt water using only solar energy | Rice University | https://www.youtube.com/watch?v=z36jMKk-AdQ (accessed on 4 January 2024) |
| Normalized Comments | 16 | 2023 | MEMBRAN DESTILASI | Anasthasya Isaura | https://www.youtube.com/watch?v=mdv7Qh-9rXc (accessed on 4 January 2024) |
| Subscribers | 685,000 | 2018 | Principle and Theory of Conc membrane process freeze concentration | Vidya-mitra | https://www.youtube.com/watch?v=ygZ4OB93ALQ (accessed on 4 January 2024) |
| Likes | 1400 | 2018 | Freshwater from salt water using only solar energy | Rice University | https://www.youtube.com/watch?v=z36jMKk-AdQ (accessed on 4 January 2024) |
| Normalized Likes | 233.33 | 2018 | Freshwater from salt water using only solar energy | Rice University | https://www.youtube.com/watch?v=z36jMKk-AdQ (accessed on 4 January 2024) |

As can be clearly seen in Table 2, the video about MD on YouTube with the highest amount of interaction in multiple categories (most views, most normalized views, most commented, most liked and most normalized liked) is "Freshwater from salt water using only solar energy" uploaded by "Rice University". In this video, Prof. Qilin Li reports on an off-grid system developed in nationally funded research on water purification that converts salt water into fresh drinking water using only solar energy. When the received comments are normalized based on the year of upload, the video entitled "MEMBRAN DESTILASI" by Anasthasya Isaura takes the first position (16 comments/year). In terms of the number of subscribers, the channel named Vidya-mitra is at the top. This channel creates lectures about different topics and, with its high subscriber value, this channel is of great importance in promoting MD to the community. We also provide information on the locations of content creators in our analyses (Figure 6). Note that only 72 of the channels have shared information about their location.

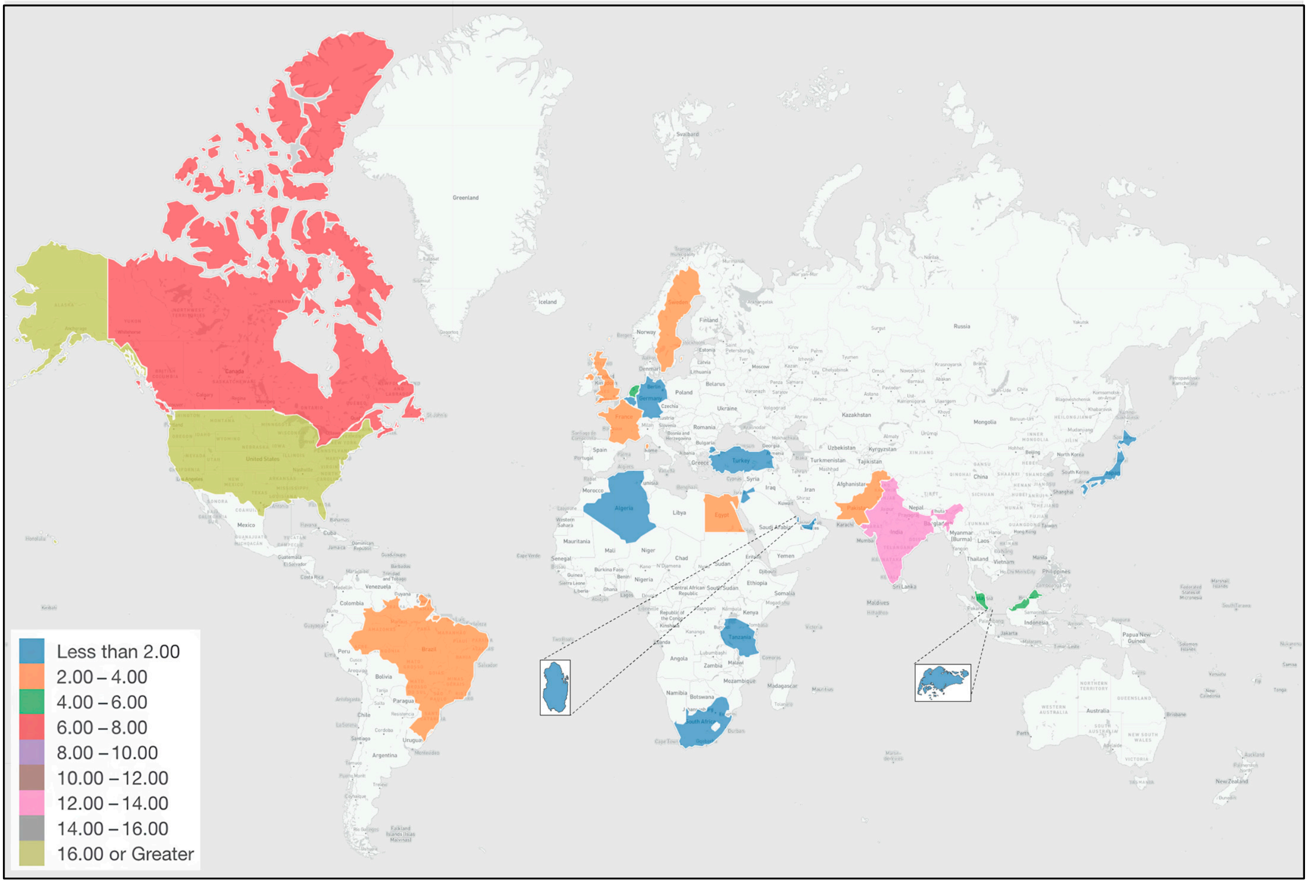


**Figure 6.** Geographic distribution of content creators producing MD-related content on YouTube.

When a type of content is dominant in a location, it means that there are people interested, there is a market for that content, and there are scientific studies, companies, and/or people willing to spread knowledge on that subject in that location. As Figure 6 indicates, the majority of channels posting content on MD are from the United States of America (18), followed by India (13) and Canada (6), which is also strong proof on the popularity of MD in these countries. This provides an important basis for the MD community to better understand the interests and needs of different geographies. MD research and education efforts should therefore be planned more effectively, focusing on these regions and collaborating with researchers from different geographies. These data should be used strategically in efforts to disseminate MD technology to address global water challenges.

Word clouds may help analysts to quickly find the most significant words in a large text collection to identify the ideas, underlying themes, and addressed topics. In this study, the word cloud method was only applied to videos with English transcripts (157 videos) to maintain consistency and the results are depicted in Figure 7.

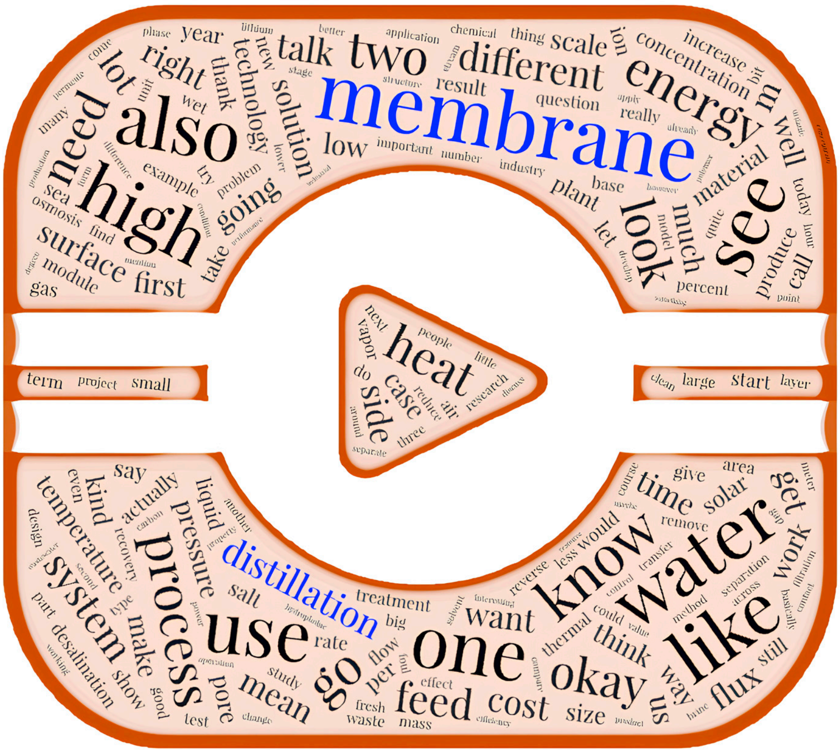


**Figure 7.** Word cloud of most frequently appearing words in MD video transcripts.

From Figure 7, it can be clearly seen that the three words most frequently used by the speakers are "membrane", "water" and "use". The fact that these three words are commonly used in the videos indicates that these videos basically share the definition of membrane distillation with their viewers. The word "separation", which appears 524 times, reveals that the videos stand out, especially in relation to membrane separation applications involving different configurations, techniques, and systems; information on separation efficiency, membrane performance, research on new membrane materials, etc. Instead of the word "separation", the narrators also frequently use the words "filtration" (403) and "purification" (62). Furthermore, the fact that the word "membrane" is mentioned ~5 times more than "distillation" (7017 and 1515, respectively) shows that the speakers in the videos emphasize the importance of membranes in the MD separation process. Other types of membrane-based separation methods are also mentioned in the MD videos. The repeated words "reverse" (453), "osmosis" (536), "nano" (242), "filtration" (403), "ultrafiltration" (64), "nanofiltration" (50), "microfiltration" (42), "electro" (77), "dialysis" (72), and "electrodialysis" (37) provide evidence that MD is mentioned alongside other separation technologies or presented to the audience in a comparative manner or in some hybrid configurations. At the same time, the frequency of the desalination method name indicates which other desalination approach is most frequently mentioned in the videos. Words such as "salt", "gas", "ion", "carbon", "lithium", "organic", "sodium", "hydrogen", "oil", "volatile", and "chloride" appear 534, 406, 376, 291, 262, 261, 244, 233, 210, 75, and 201 times, respectively. These words are mentioned by the narrators to show that MD technology can be used to separate different components present in water/wastewaters. The fact that the words "temperature" (1194), "heat" (1030), "solar" (657), and "thermal"

(545) appear in the word cloud graph reveals that the energy requirement of MD separation and the resources that can provide the necessary energy for MD systems are also of utmost importance and must be conveyed to the audience. Membrane fouling and concentration polarization are among the most critical problems in membrane separation processes. The words “fouling”, “concentration”, and “polarization” appear 291, 892, and 188 times in the transcripts, respectively. This indicates that these issues are also addressed in the videos. Membrane is the core of any membrane separation process, including MD. Basically, three membrane types are involved in MD studies: flat sheet, nanofiber, and hollow fiber. The words “flat” (76), “sheet” (102), “hollow” (128), “fiber” (250), “fibre” (2), “nanofiber” (27), and “nanofibrous” (5) are also addressed in the word cloud, indicating that the membrane type is also mentioned in the videos. It is also seen from the word frequency that the type of membrane most frequently reported in the videos is hollow fiber. The topics covered in the videos are not limited to membrane types only; the frequent use of words such as “polymer” (366), “polymeric” (76), “coating” (120), and “hydrophobic” (419) also shows that information is conveyed to the audience in the field of polymeric materials engineering. Again, the fact that words like “permeation” (41), “diffusion” (166), “osmosis” (536), “concentration” (892), “rejection” (166), “flux” (738), “pore” (568), “size” (586), “adsorption” (23), and “temperature” (1194), which are important factors affecting the separation efficiency, appear in the word cloud is evidence that the narrators conveyed full details about the MD process involved in the videos.

In addition, as expected, the words “air” (353), “gap” (272), “direct” (148), “contact” (282), “vacuum” (149), “sweep” (25), “sweeping” (19), “liquid” (718), “permeate” (401), “submerge” (11), “flash” (33), and “material” (844) are also present in the word cloud. These are related to the different MD configurations that should be covered in the videos. Furthermore, a detailed search of the transcripts was also conducted to identify how many times a configuration was discussed in the videos. According to the full configuration name and the corresponding abbreviation search of the transcripts, DCMD, VMD, AGMD, SGMD, LGMD/PGMD/WGMD, VEMD, MGMD/CGMD, and submerged membrane distillation were mentioned in 26, 19, 14, 6, 4, 2, 1, and 1 videos, respectively. MD research is constantly evolving to achieve the best possible system design and performance. As a result, MD scientists outdo themselves every year in terms of creating new MD membranes, modules and systems. But it is not surprising that some main configurations (e.g., DCMD, VMD, AGMD, and SGMD) are more popular or more researched in MD studies, resulting in more video content being published about these main configurations. This is because these configurations have been researched for many years and their use has been demonstrated in many applications. Some configurations (LGMD/PGMD/WGMD, VEMD, and MGMD/CGMD) have fewer videos because these are relatively new and hybrid MD variants based on the four previously mentioned configurations. Less content has likely been produced because these innovative configurations involve complex technology, have not reached technological maturity yet, and have less applicability as a consequence. This limitation should be taken into account when interpreting the results. We invite the MD community to upload videos about innovative MD configurations and especially about VAGMED, VEMD, TSGMD, sub-atmospheric AGMD, and flashed-feed VMD variants to let the water sector know how progressive MD technology is.

Sentiment and emotion analysis of viewer comments informs analysts about how viewers react to the content of videos and what to consider in future uploads. Figure 8 contains sentiment and emotion analyses of comments on MD-related videos. For these analyses, comments and reactions/emojis in English were evaluated (204 comments in total). Since the emotion model can only be used with data points that have fewer than

512 tokens, 203 comments were used in the procedure. The figure includes kernel density plots of the results and pie plots of the dominant sentiment/emotion.

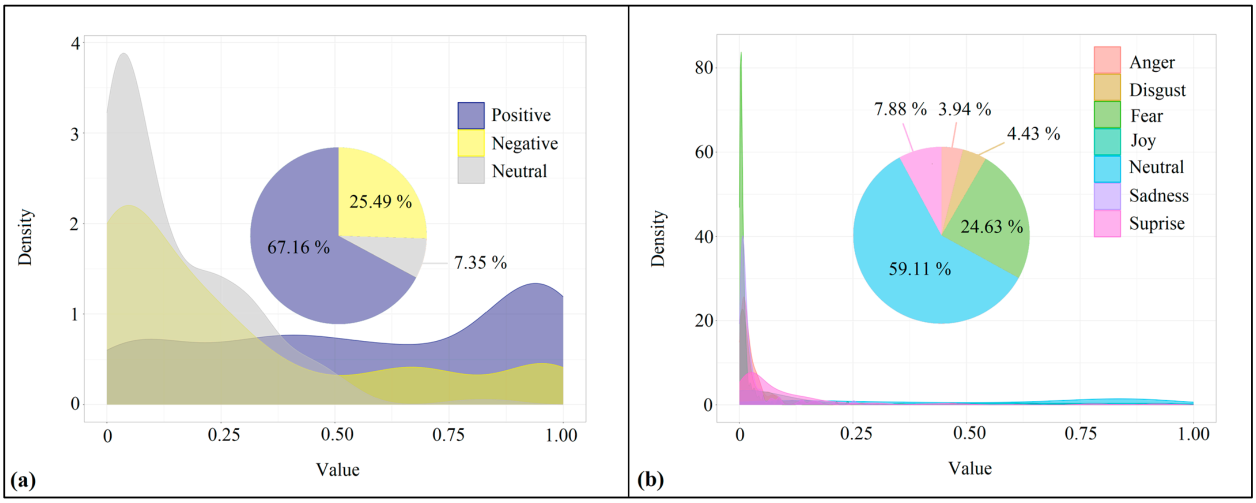


**Figure 8.** (**a**) Sentiment and (**b**) emotion analysis of the comments on MD videos uploaded on YouTube.

The sentiment results in Figure 8a indicate that most of the commenters (67.16%) have positive opinions about the MD video content, while only 25.49% of the comments are negative, and the rest are neutral. Considering this result, we see that viewers of MD videos enjoy them and have a positive experience. The sentiment outcomes also reflect the quality of the MD-related videos and the viewers' satisfaction. As shown by the emotion analysis results in Figure 8b, most of the comments (59.11%) are neutral (no mood). The second most common emotion is joy (24.63%), meaning that commenters show great pleasure and happiness about MD technology. The percentage of those who were surprised by MD was 7.88%. The commenters who were surprised were likely those who were hearing about this technology for the first time. Few viewers expressed anger and disgust, and no commenters expressed fear or sadness when watching videos about this technology. The result of emotion analysis reveals that the channels that will create MD-related videos should increase the joy of more viewers. This will raise awareness and trust in MD technology and ensure that it will be the first separation process that comes to mind for obtaining drinking water from saline water in the coming years.

In this study, we also introduced a concept known as the narrative intensity ($NI$) of a video. It was calculated using Equation (5) and represents the ratio of the number of words used in the video's transcript to the duration of the video (i.e., the number of words per second). It is a way of showing how much information a video conveys. *NI* enables us to identify critical points of information dissemination and evaluate the effectiveness of communication in each video. Knowing the significance of *NI* can help content developers adapt their videos to better meet the tastes and information needs of their target audience. Narrative intensity can be very important for capturing viewers' attention, increasing the information transfer efficiency, adapting to the target audience, and planning the video in general. Rather than simply providing more information, *NI* should be carefully managed. For example, narrative intensity can be kept high in videos intended for a technically savvy audience, as they may want to learn more information more quickly. However, for videos that appeal to a more general audience, it may be more effective to keep the narrative density low and present it in a simpler and clearer way. Content producers can use transcript analysis tools to measure narrative density, divide their videos into different segments, adjust the narrative density accordingly, adapt it to the knowledge level of their target audience, and improve video quality through feedback. In this way, narrative density becomes a tool used not only to provide more information, but also to convey it more effectively and to help the audience learn better.

For visualization of the narrative intensity results, we only used videos that are narrated in English. This is because some languages have a structure based on separate words and spaces, while other languages are character-based and often have no spaces between words. In addition, since different languages have different alphabets, English, the language used in the highest number of videos, was used for consistency in the analysis. The result is shown in Figure 9, with a heatmap including 157 data instances.

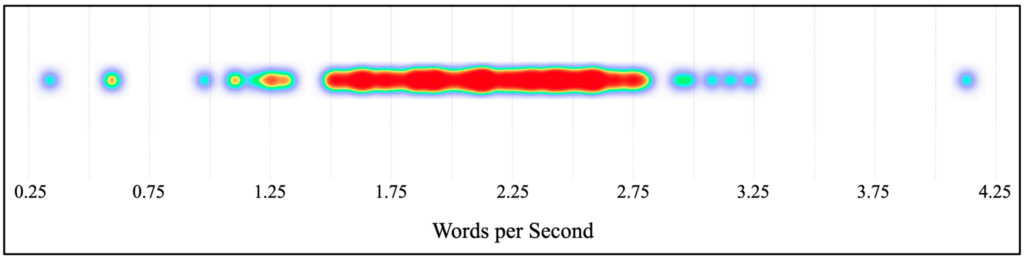


**Figure 9.** Narrative intensity (words/s) heatmap of MD-related YouTube videos in English.

In Figure 9, the red areas represent the hot spots where the narrative intensity is high. Most of the videos have a wide range of words per second, going from 1.5 to 2.8. The average value is ~2.12 word $s^{-1}$, which serves as a reference point, indicating the typical narrative intensity across all analyzed videos. The highest registered *NI* value is 4.13 word $s^{-1}$. This type of material is likely to be impactful because of its compact and information-rich presentation, which keeps viewers engaged with a steady stream of knowledge. On the other hand, at ~0.34 word $s^{-1}$, the least narratively intensive video registered may highlight other factors, such as graphics or emotional storytelling, making it engaging in a number of ways. It is worth noting that people use YouTube for much more than just entertainment, but also for their education. Therefore, we recommend that trainers and educators use longer MD videos. Content creators should develop interesting and informative MD videos and convey more information in longer videos instead of shortening the duration to increase the *NI* value.

## 4. Conclusions

Visual social media plays an important role in our lives because it enables the rapid and comprehensive transmission of information via images and videos. YouTube, the largest video-sharing platform on the web, has become a vital tool for information, entertainment, and communication due to its vast collection of videos and its ability to reach millions of people. This study examines the status of MD on YouTube using a set of basic statistical, natural language processing, and machine learning approaches. We found that some insights from the collected dataset, such as the number of videos (212), timespan (2011–2024), total duration (80 h 33 m 9 s), total comments (207), total views (379,772), and total likes (4340) express the inadequacy of the MD's representation on YouTube. The number of MD videos uploaded annually is proof of this insufficient publicity on social media. English dominates the narrative and comments sections of the videos. The video entitled "*Freshwater from salt water using only solar energy*" from Rice University is the leading video in terms of viewer engagement, with statistics such as 148,000 views, 24,467 normalized views, 54 comments, 9 normalized comments, 1400 likes, and 233 normalized likes. The word cloud approach to the transcripts reveals that "membrane", "water", and "use" are the dominant words in the MD videos. The word "separation" was used 524 times by narrators. The sentiment results indicated that 67.16% of the comments were positive about MD. The analysis of emotions revealed that a neutral mood was the most common emotion in the generated comments, with a contribution of 59.11%. Although the MD process has an important place among separation technologies, in this study, the analysis of the results shows that there is a lack of content on YouTube related to MD and the findings have important implications for some areas of MD. The findings in the present study can help content creators involved in MD research and educational outreach. In terms of MD research, our findings can guide researchers' focus by identifying the topics that receive more attention on social media. More videos are needed, especially on underrepresented MD configurations, membranes, and modules engineering research. Posting videos on YouTube about these under-researched MD configurations can help content creators stand out by making a difference, building an image of expertise, creating engaging and original content, having a social impact, etc. The locations of published videos can encourage researchers and investors to focus more on these areas. Identifying widespread misinformation or incomplete information about MD on social media highlights the importance of research based on accurate information. In terms of educational efforts, our findings highlight the need to communicate about MD more effectively on social media. The importance of the video format and the English language is noteworthy. Identifying topics on which viewers lack knowledge and are confused should be taken into account in the preparation of future MD videos. Analyzing emotional reactions in comments can help us understand the impact of educational video content on viewers.

## 5. Limitations and Future Directions

The current study is a comprehensive analysis to assess the social media coverage of membrane distillation (MD) content on YouTube, but the authors are aware of the limitations. The dataset was created by manual searching for videos, which may have introduced possible biases. The selection of search terms and the researchers' own evaluation criteria during the manual screening process could also create possible problems. Biases caused by manual screening can be reduced by using more advanced and automated methods. Furthermore, by using different sentiment analysis models, different interpretation results can be compared, and thus bias in some results can be reduced. Our study was limited to the YouTube platform and MD content on other social media platforms (e.g., Instagram, TikTok, LinkedIn, Facebook, Twitter) was not included in the analysis. This limited the opportunity to examine the different ways MD is presented and audience behavior on different platforms. As different services target different audiences (professionals, politicians, and the public) and host different debates about MD, limiting ourselves to YouTube alone may have led to generalizability issues. Data were collected on 4 January 2024. The results of the analysis may change over time due to the dynamic nature of content on YouTube.

Future studies should aim to overcome these limitations and assess the reflection of MD on social media more broadly. For this purpose, more comprehensive datasets can be created using broader search terms. Comparing MD content on different social media platforms and analyzing different aspects can help provide a deeper understanding of this topic. Future studies should also assess viewer engagement rather than focusing only on video content. Additional data collection methods such as surveys and focus group discussions can be used to better understand audience perceptions and attitudes towards MD technology. Finally, as this study covered a specific time period, it would also be useful to conduct longer-term studies to understand how the MD trend on social media platforms evolves over time.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| AGMD | Air gap membrane distillation. |
| API | Application programming interface. |
| CAGR | Compound annual growth rate. |
| CGMD | Conductive gap membrane distillation. |
| DCMD | Direct contact membrane distillation. |
| ED | Electrodialysis. |
| FO | Forward osmosis. |
| GS | Gas separation. |
| JSON | Java Script object notation. |
| LGMD | Liquid gap membrane distillation. |
| MAS | Membrane air stripping. |
| MBR | Membrane bioreactor. |
| MCr | Membrane crystallization. |
| MD | Membrane distillation. |
| MF | Microfiltration. |
| MGMD | Material gap membrane distillation. |
| ML | Machine learning. |
| NC | Number of comments. |
| NF | Nanofiltration. |
| NI | Narrative intensity. |
| NL | Number of likes. |
| NLP | Natural language processing. |
| NV | Number of views. |
| PGMD | Permeate gap membrane distillation. |
| PV | Pervaporation. |
| RED | Reverse electrodialysis. |
| RO | Reverse osmosis. |
| SARSA | State–action–reward–state–action. |
| SGMD | Sweeping gas membrane distillation. |
| TO | Thermos-osmosis. |
| TSGMD | Thermostatic sweeping gas membrane distillation. |
| UF | Ultrafiltration. |
| VAGMD | Vacuumed air gap membrane distillation. |
| VEMD | Vacuum-enhanced membrane distillation |
| VMD | Vacuum membrane distillation. |
| V-MEMD | Vacuum multi-effect membrane distillation. |
| WGMD | Water gap membrane distillation. |

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