A multi-aspect analysis of echo chambers on video-sharing social media

Omran Berjawi[1[0009−0008−6763−9630]], Danilo Cavaliere[2[0000−0003−2859−0447]], and Giuseppe Fenza[2[0000−0002−4736−0113]]

[1] IMT School for Advanced Studies Lucca, Piazza S.Francesco, 19, 55100 Lucca (LU), Italy omran.berjawi@imtlucca.it
[2] University of Salerno, Via Giovanni Paolo II, 132, 84084 Fisciano (SA), Italy {dcavaliere, gfenza}@unisa.it

Abstract. Video-sharing platforms, including YouTube and TikTok, have changed the way people consume media by creating dynamic online communities driven by content recommendations. While these platforms enrich user experience, they also risk confining users within echo chambers, where content reinforces existing beliefs. This study addresses the challenges of identifying and understanding echo chambers by introducing four indicators that reflect various aspects of user behaviours within online communities. These indicators encompass linguistic patterns, ideological closeness, and content consumption habits. The primary objective is to employ these indicators to discern the presence of echo chambers based on user behaviors within any given community. By applying these indicators to a publicly accessible dataset, the contribution of this work is twofold: firstly, to track changes in user behaviours as echo chambers evolve over time, secondly, to conduct predictive experiments aimed at assessing the efficacy of these indicators for predicting variations in users decision by means of staying and leaving their communities. The main findings highlight the significance of these indicators for understanding the dynamics of echo chambers and provide insights that are relevant for helping professionals to monitor these phenomena. The approach offers a promising direction for proactive strategies in managing content diversity and reducing polarization on social media platforms.

Keywords: Echo Chambers · Social Behaviors · Video Preference Prediction · Online Polarization.

1 Introduction

Video-sharing social media platforms, such as YouTube, have completely changed the way users interact with content, fostering dynamic communities and diverse forms of engagement way. Users on these platforms not only consume videos but actively interact with each other through likes, comments, and shares. The algorithms employed by these platforms aim to personalize content recommendations based on user content preferences, creating a tailored experience for each individual. However, this customization has its drawbacks since it can lead to the formation of closed environments called echo chambers. The echo chamber phenomenon occurs when individuals are exposed to information or opinions that reinforce their existing perspectives [10] and surrounded by like-minded individuals who share similar opinions. These so-built communities are close to new and alternative-thinking information circulating outside the community. This environment forces people to strengthen pre-existing biases that lead them to spread misinformation [4], and increase social polarization [6].

Detecting echo chambers in social networks requires analyzing complex patterns, including user language similarity (e.g., shared vocabulary and ideological jargon), user interactions in video comments, and group relationships (i.e., joining a community about a specific topic). Understanding these dynamics would help spotting user alignment with specific communities using similar language and interaction patterns. Unfortunately, existing approaches for unveiling echo chambers tend to exclusively focus on certain features or aspects [11], [17], [7]. As a consequence, these solutions may not fully capture echo chambers on social media platforms. Moreover, it would be challenging to understand if these aspects are related to the formation of echo chamber and at which extent. Moreover, social media monitoring experts also demand solutions to analyze and forecast eventual evolutions of communities that requires advanced analyses of user behaviors whenever he/she decides to change community (i.e., when he/she leaves or stays within a community where members start to share the same political believes [15]). Therefore, to properly detect echo chambers, there is the need for understanding the role of the above-mentioned aspects (e.g., user language similarity, user interactions, etc.) in the estimate of community membership changes.

To deal with this challenge, this study explores user behaviours within user groups or communities and evaluate the advantage of using such behaviors to determine echo chamber presence. To do so, the study aims to answer the following research questions:

- RQ1: How can user behaviors serve as indicators to monitor echo chamber evolution over time ?
- RQ2: To what extent can user behavioural indicators be used to predict the changes in their preferences and decisions ?

To answer these questions, this paper introduces a pipeline including graph network, node embedding and clustering. The pipeline offers a two-pronged contribution to understand user behaviours within echo chambers. Firstly, by proposing and analysing four indicators that reflect various aspects of users behaviours within their communities. The experiment sheds light on changes in user behaviours in terms of linguistic patterns, ideological closeness, content consumption change as echo chambers evolve. Secondly, the study analyzes the power of the proposed indicators for predicting changes in user decision in terms of staying and leaving their communities. This integrated approach not only enhances the ability to understand and predict user engagement within echo chamber environments, but also offers a promising avenue for an early identification of behaviours that would lead users to join echo chambered communities and prevent the spread of radicalization.

The rest of the paper first presents related work discussion (Section 2), then Section 3 introduces the methodology. Finally, experiments (Section 4) and result discussions (Section 5) about the validity of the indicators are presented, hence conclusions close the paper.

2 Related work

Determining the presence of echo chambers is a not trivial task that has been analyzed on various social networks and with different methods. The main research directions are focused on extracting meaningful trends to understand the echo chamber formation and evolution by analyzing a specific topic in a social network environment. Other research trends are based on measuring echo chamber presence by proposing metrics based on the network topology built on specific relationships representing different semantics (i.e., friendship, mentions, follower/followee, etc.) [11].

Capturing user interaction for echo chamber assessment in YouTube platforms is way more complex than in other types of social platforms since users interact over videos through comments and replies [12]. In fact, YouTube users tend to follow content recommendations based on their history interactions instead of exclusively following the contents of their friend. Research on these media mainly focused on exploratory video consumption studies, such as the work of Di Marco et al. [17], that analyzes information flow on YouTube during Covid19 pandemic, observing a relation between the political bias of users and their tendency to consume highly questionable news. Another work [8] exploits graphs to represent users' interactions over comments to YouTube videos by embedding their position towards the video topic (e.g., dominant, divergent, etc.). Another study [20] explores the influence related to users' imitation, intergroup interaction, and reciprocity behavior on echo chambers using network graphs and determining the presence of echo chambers according to users' positions towards topics.
Other works focused on specific types of features to quantify echo chambers, such as the research of Kratzke [14] that investigated retweet interaction network to develop a greedy modularity for detecting communities, and the authority values to estimate echo chamber presence. Another example is the method proposed by Yichang et al. [7] that focuses on social network analysis and sentiment analysis to measure selective exposure and homophily in short video platforms (i.e. TikTok).

Other researchers further explored YouTube, on which recommendations play an important role in leading users into filter bubbles and eventually in echo chamber environments. In this regard, some research directions, such as the work by Lutz et al. [16], that employs Natural Language Processing (NLP) techniques to analyze the political bias within search and video recommendation algorithms. Another work [13] investigates the influence of recommended videos on echo chambers and polarization by analyzing the structure of recommendation networks.

In contrast to previous approaches focusing on a single specific feature (e.g., political bias [17], retweet interaction network [14], etc.) this study analyzes a combined use of indicators covering different kinds of user own features, network and content aspects to better quantify the presence of echo chambers. It examines factors such as user language similarity, content type, and comment-based interactions and aims to find out the relevance of those parameters for evaluating echo chamber presence. Additionally, it aims to extend existing literature by exploring diverse indicators to predict variations in echo chamber level based on community membership changes in echo chamber contexts.

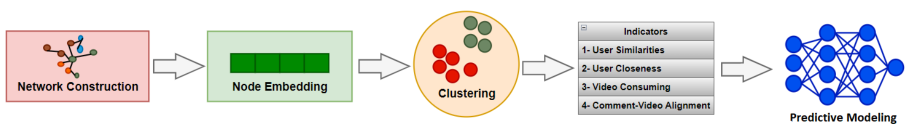

Fig. 1. The methodology includes network construction, node embedding, unsupervised clustering, indicators assessment and user behavior prediction.

3 Methodology

This section introduces the methodology employed to build the indicators for describing users and their activities. It has been designed as a multi-faceted approach that takes into account user comments, and calculate four indicators to describe user language features, behaviors and user interactions over video content to predict future community membership changes useful to evaluate echo chamberness. The complete pipeline is shown in Figure 1 reporting five main components: Network Construction, Node Embedding, Clustering, Indicators Assessment, and User Behavior prediction. The rest of the section will first introduce the data which the approach is built over, then the components of the pipeline mentioned above will be presented in detail.

3.1 Dataset Description

The dataset used for the experiments was gathered by Ribeiro et al. [19]. It comprises various videos and classified into different political categories. The focus has been set to right-wing communities within the dataset commenting on videos labeled as Alt-lite and Alt-right cateogires which are generally associated with strong echo chambers. The dataset was divided into three time frames: 2016, 2017, and 2018; based on comment dates and including users who consistently commented across all three time frames. The resulting subset includes 2,786 unique users and contributing to a total of 671,030 comments on 9,001 videos. Table 1 provides a summary of the dataset used for the tests.

Category	Value
Videos	9,001
Number of comments	671,030
Number of unique users	2,786

Table 1. Dataset Summary

3.2 Network Construction

The first stage in the displayed pipeline is devoted to network building. Three unweighted interaction networks were built, each one corresponding to a snapshot covering a specific period (time frame), hence the achieved graphs allow to see user interactions across time frames. Let $G_i = (V_i, E_i)$ be the graph for the i^{th} frame, where V_i stands for social media users and the edges in E_i represent the users' replies to other users' comments on a video. User comments have been used as an attribute for every node in order to enhance data representation semantics.

3.3 Node Embedding

Once the networks are built, a graph neural network approach has been adopted to capture user activities within each network by embedding into low-dimensional representation the combination of both the structural information of user interactions and the semantic content extracted from user comments. Our approach is an adaption of the *GraphSAGE* framework [9], which was originally intended to carry out structured graph node embedding through the sampling and aggregation of node neighborhood data.

As illustrated in Figure 2, our model consists of multiple *SAGEConv* layers, with each layer being followed by a rectified linear unit (ReLU) activation and batch normalization. It takes two components in input as represented in Figure 2: (A) represents the adjacency matrix of the constructed graph, and (V) is the embedded vector of user comments. BERT has been used [5] to generate a representation for each comment text and then used pooling to generate an

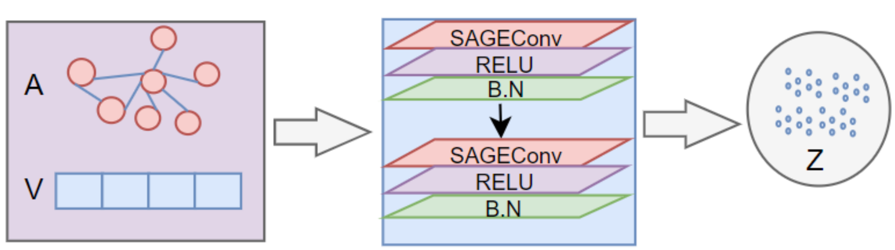

Fig. 2. GraphSAGE take two components as input, the adjacency matrix (A), user text embedding (V) and resulting with user embedding (Z)

embedding representation (V) for each unique user. The resultant embeddings provide insights into the traits and behaviors of the individual in each time frame.

3.4 Clustering

To further analyze and interpret the embeddings, k-means clustering has been run on the resulting embedding vectors. This embedding supports community detection exploiting the analysis of individual features. Therefore, the extracted clusters are the communities based on the embeddings. Then, the elbow method has been employed to determine the optimal number of clusters (K) in three different time frames. Remarkably, the elbow plot analysis consistently revealed that K=2 is the optimal number of clusters across all three time frames. To assess the performance of our clustering, a silhouette score has been used to ensure high clustering analysis quality and distinctiveness of the identified communities. The achieved results will be discussed later on in the experimental section. After that, Latent Dirichlet Allocation (LDA) has been used for topic extraction aimed at labeling each cluster within each time frame. By using LDA, each cluster is associated with specific topics, ensuring to keep consistency in cluster interpretation across different years. Consequently, cluster 0 labeled with topic t in 2016 can be reliably compared to cluster 0 labeled with topic t in 2018, as the clusters are defined based on the topics extracted through LDA. This strategy allows to see if labeled users have changed community over the years by looking at labeled clusters they were in in previous years.

3.5 Echo Chamber Indicators

In evaluating indicators for assessing the evolution of echo chambers, various indicators have been considered to represent the characteristics that thoroughly depict user behaviors and community dynamics identified in the earlier stage. In detail, this approach considers four key indicators: language similarity among users, a user position within their community, the content consumed by the user and the connection between user comments and video topics. Let us introduce them in more detail in the rest of this section.

User Similarity (Sim). The first indicator is the language pattern of users within communities, which is regarded as a way of communicating ideas and feelings that greatly influence people's attitudes. This specific indicator aims to quantify the similarity in the user language, serving as a measure of the homogeneity within a community. An increased homogeneity is often associated with polarized groups and echo chambers. The method involves employing cosine similarity to measure average linguistic similarities among users. As a first step, the average similarity for each user is computed as follows:

$$\mathrm{Sim}_i = \frac{1}{2}\left(\frac{\sum j = 1^{N_C} \mathrm{C.S}(u_i, u_j)}{N_C} + 1\right) \tag{1}$$

Then, user comments are embedded by using BERT, and similarities are calculated between the embeddings of each user and all other users within the same community. The values are normalized on the total number of users in the community. Finally, the average cosine similarity for each community is determined as follows:

$$\mathrm{AvgSim}_C = \frac{1}{N_C} \sum_{i=1}^{N_C} \mathrm{Sim}_i \tag{2}$$

where N_C represents the number of users in the community, and $\mathrm{C.S}(u_i, u_j)$ is the cosine similarity between user u_i and user u_j.

The score AvgSim_C lies within the $[0, 1]$ range, so 0 means no similarities between users within a particular community, whereas 1 stands for a significant degree of similarity among community members.

User Closeness (UCL). The second indicator is the user closeness which measures the closeness among users within their community. To this purpose, the cluster centroid has been considered the most representative point of the ideology present in the community, also indicative of a more extreme or focal viewpoint. In this context, this indicator aims to study the movement of users toward the centroid which illustrates the trend of users adopting increasingly radical viewpoints. This trend points out a stronger user adherence to the dominant ideology within the group. Formally, the user closeness score is defined as follows:

$$UCL_i = \mathrm{dist}(\mathrm{Centroid}_{C_1}, \mathrm{U}_i) - \mathrm{dist}(\mathrm{Centroid}_{C_2}, \mathrm{U}_i) \tag{3}$$

where $\mathrm{dist}(\cdot, \cdot)$ represents the Euclidean distance function, explicitly indicating the calculation of the distance between the embedding vector of user i (U_i) and the centroids of their respective communities ($\mathrm{Centroid}_{C_1}$ and $\mathrm{Centroid}_{C_2}$). The resulting UCL_i ranges between -1 and 1, where -1 indicates the user is more attracted to the centroid of their community (C_1), as compared to the centroid of the other community (C_2). When users move closer to the centroid, there is a greater alignment with the group prevailing ideology.

Video Consumption Score (VCS). The third indicator represents the type of videos watched by users, acting as an insightful metric to gauge user preferences and consumption pattern. For instance, when a user leaves a comment to a video, it implies he/she has consumed this content due to his/her interest in the video content. The proposed score not only quantifies user preferences for specific video categories, but also provides valuable insights into the dynamics of content consumption within the communities and how much a user interacts with a certain video category. The Video consumption Score (VCS_i) is defined as follows:

$$VCS_i = 1 - \frac{Total_{Ct_1}}{\mathrm{Total\_Comments}} \tag{4}$$

where $Total_{Ct_1}$ represents the number of comments posted by a user on category Ct_1. This score offers a numerical result that ranges from 0 to 1, where

0 implies exclusive consumption of Ct_1 videos, while 1 stands for exclusive engagement with other video categories. In the experiments that will follow, the indicator has been considered to depict engagement with two video categories, but it can be also employed to assess consumption on more than two video categories.

Comment-Video Alignment Score (CVS). The last indicator to be considered is the Comment-Video Alignment Score (CVS) as an indicator encapsulating the degree of alignment between user comments and the corresponding video. Let us remember that different users engage with various videos, hence the cosine similarity is assessed between the video description and each comment related to it. The resulting CVS score falls within the $[-1, 1]$ range. A score of 1 signifies a perfect alignment between the user comment and the video description, 0 indicates no alignment, and -1 suggests an opposite alignment. This score allows us to precisely quantify the semantic congruence between the user and the video context he/she commented on. The indicator is formally defined as follows.

$$\mathrm{CVS}_i = \mathrm{C.S}(C_i, V_j) \tag{5}$$

where $\mathrm{C.S}(C_i, V_i)$ is the cosine similarity between the j^{th} video description and the i^{th} comment text.

3.6 User behavior prediction

In the final stage of the proposed approach, there is a prediction model aimed at processing the above-introduced indicators as features to predict if users will change communities. With this purpose, our DNN model, comprising five layers with 1024, 256, 128, 32, 16, and 1 neurons respectively, ReLU activation functions were applied in the hidden layers, and a sigmoid activation function was used in the final layer. This architecture is chosen for its ability to capture complex patterns. The model objective is to classify users based on their inclination to either stay in their current community or move to another one.

4 Experiments & analysis

This section discusses experiments for assessing the validity of the proposed indicators for examining echo-chamber dynamics on video-sharing platforms and their utility for predicting community changes. This section reports experiments consisting in testing the effectiveness of proposed indicators for studying echo-chamber dynamics and predicting user decisions. The rest of the section describes data preparation and two experiments. The first experiment evaluates the use of the indicators for analyzing the echo chamber status, while the second experiment analyzes changes in user video consumption and assesses the accuracy of predicting user decision using the proposed indicators.

4.1 Data preparation

To generate the data for the experiments, three unweighted interaction networks have been created, each one corresponding to a distinct period. The network configurations for these time frames are as follows: In 2016, there were 2786 users and 2200 edges; in 2017, there were 2786 users and 3843 edges; and in 2018, there were 2786 users and 4904 edges. Then the *GraphSAGE* model has been run to perform node embedding. First, the user comments have been pre-processed, including cleaning and tokenization, followed by BERT-based embedding to capture rich semantic information. At the same time, the network adjacency matrix is defined to encode interactions between users. These two components are integrated as input features for the *GraphSAGE* model. After that, K_means is run to classify the node embedding produced by the model generating two clusters for each time frame, and where each cluster in the three time frames represents the same community. In clustering results, the number of users in Cluster 0 decreased from 1,885 nodes in 2016 to 1,530 nodes in 2018, while in Cluster 1, increased from 901 to 1,256. This trend means a concurrent process of expansion and pruning in user numbers within both clusters.

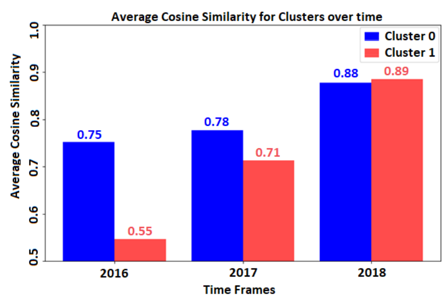

Fig. 3. User similarities results

4.2 Indicators relevance for echo chamber assessment

To evaluate the relevance of our indicators for assessing echo chambers, let us observe the correlation between the indicators and a state-of-the-art metric called the Echo Chamber Score [1] which measures the distances between users in the embedding space in order to evaluate the cohesiveness and separation of user communities. This metric is first calculated for each time frame. The ECS results reflected the evolution of echo chamber dynamics inside the detected clusters over time that characterized by an ascending trajectory, from 0.8003 in 2016 to 0.8114 in 2017 and further to 0.8417 in 2018. Then, the correlation between each indicator and the ECS is calculated by using Pearson correlation coefficient. Let us give a look at each indicator one-by-one considering firstly their distribution on network users, and then their correlation with ECS score.

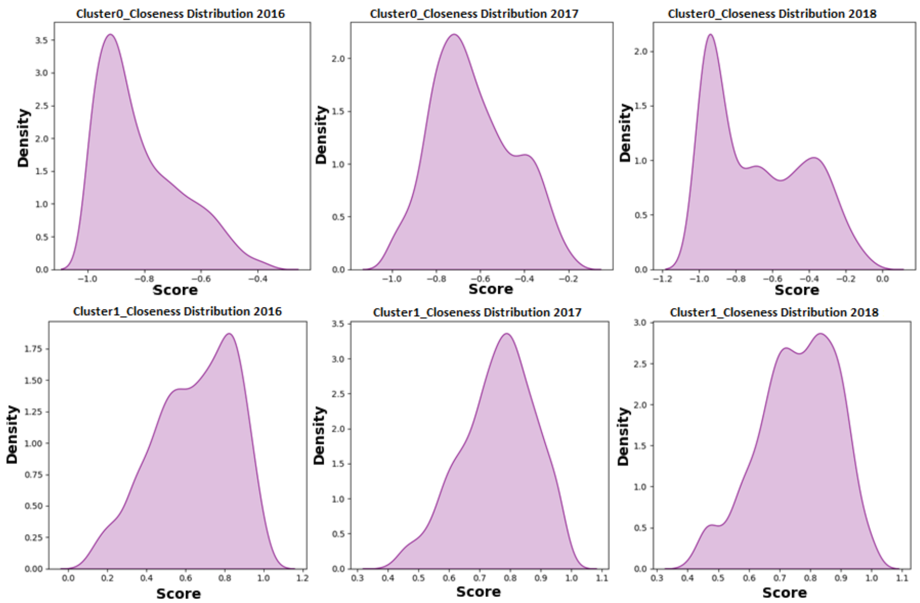

Fig. 4. User closeness score distribution (density) for each cluster

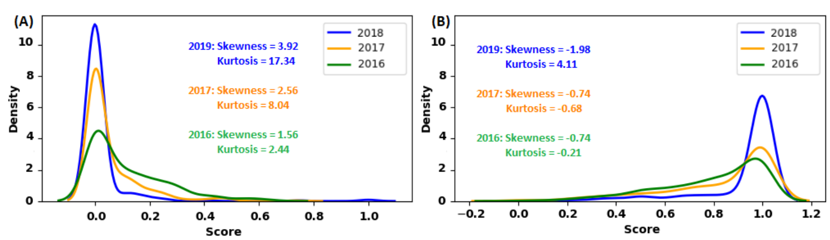

Fig. 5. (A) Represent the Video Consumption Score (VCS) distribution for cluster 0, and (B) the distribution for cluster 1.

User Similarity. The average similarities for each cluster were determined by using Equation (2). The results are reported in Figure 3, from which let us notice that both clusters show a constant increase in similarity from 2016 to 2018, with Cluster 1 showing a steep increase with respect to Cluster 0.
Let us now analyze the correlation results between the similarity indicator and the ECS by looking at Table 2. The indicator has a strong positive connection with ECS on both clusters. It is worth noting that the temporal dimension demonstrates that when user language changes, there are dynamic fluctuations in echo chamber intensity.

User Closeness. The closeness indicator has been calculated by using Equation 3. The resulting score trends are displayed in Figure 4 which allows us to observe how user closeness evolved for Clusters 0 and 1 from 2016 to 2018. Cluster 0 has higher dispersion, implying a variety of user positions. Even with the dispersion, the distribution peak remains within the $[-0.8, -0.7]$ range. Cluster 1, instead, has a growing trend in proximity ratings, which means that more persons gathered around their centroid in 2018 and a tendency toward more coherence within Cluster 1.
Let us examine the correlation between the average closeness and the ECS reported in Table 2, from which comes out a clear highly positive correlation between both clusters and ECS. This trend highlights the impact of user position on the assessment of the echo chamber. In other words, the plot reveals that when users ideologically move toward the center of the community they belong to, the echo chamber intensity increases.

VCS. To measure video consumption, VCS indicator is calculated according to Equation (4). The distribution of this score on the network users is analyzed by using shape metrics, including the skewness and kurtosis [2],[18],[3]. The skewness represents the asymmetry distribution, while kurtosis measures distribution peaks denoting concentration around the peak with high values. The results reported in Figure 5 clearly reveal that both user clusters show a more concentrated distribution around the peak from 2016 to 2018. Moreover, from the analysis of the skewness values, let us notice that users become more skewed in 2018 compared to 2016, leaning towards both the left and right sides. The correlation results between VCS and the ECS in Table 3 imply a larger positive association with kurtosis in both clusters. Notably, cluster 0 shows a significant positive association with skewness values, but cluster 1 shows a higher negative correlation. The high correlation on kurtosis values represents a more concentrated and peaked distribution, whereas positive or negative skewness within a cluster suggests a bias toward specific content. Overall, higher kurtosis levels and skewness, whether negative or positive, are associated with a stronger echo chamber effect.

CVS. Equation (5) was used to compute the CVS. Similarly to VCS indicator, shape metrics have been employed to examine the CVS distribution; the findings reveal a random distribution for both clusters over time, with no intriguing outcomes that can be used to describe user community change. According to Table 3 showing the correlation between CVS and ECS, let us notice a negligible

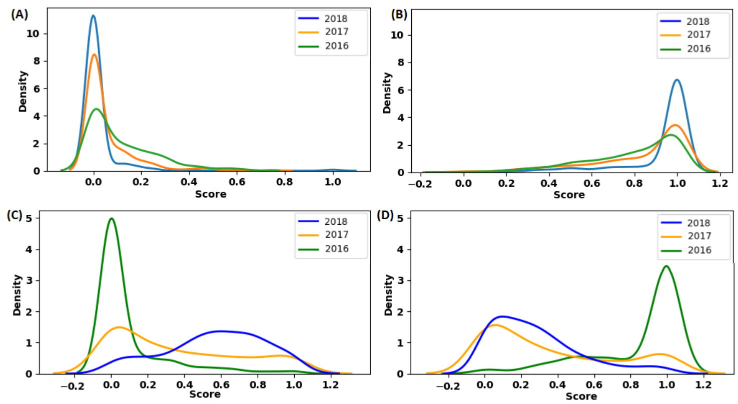

Fig. 6. (A) and (B) represent the users that stayed over the three-time frame in cluster 0 and cluster 1 respectively, (C) represents users that moved from cluster 0 to cluster1, and (D) represents users that moved from cluster 1 to cluster 0

	ECS	
	Cluster 0	**Cluster 1**
avgSim	0.95	0.97
avgUCL	0.88	0.93

Table 2. Correlation with ECS for avgSim avgUCL

correlation between kurtosis and skewness in both clusters, implying that CVS has a weak influence in the echo chamber assessment at the community level.

Based on these results, the correlation findings demonstrated the varying influence of the proposed indicators. Let us remark that the User similarity, closeness, and VCS indicators have a substantial association inside both clusters. In contrast with these indicators, the last one (CVS) has a minimal association with ECS, implying its small relevance for estimating the echo chamber status. As a result, these differences show that the first three indicators are more reliable to understand changes in communities within echo chamber environments at collective level. In contrast, the last indicator may be more appropriate for evaluations at the individual level providing insights into the subtle behaviors and preferences of single users within communities they are in, such as video viewing behaviours and biases.

	ECS			
	Kurtosis		**Skewness**	
	Cluster 0	**Cluster 1**	**Cluster 0**	**Cluster 1**
VCS	0.87	0.89	0.84	-0.93
CVS	-0.17	-0.24	-0.03	-0.25

Table 3. Correlation with ECS for the VCS and CVS indicators.

4.3 Indicators utility for predicting community membership changes

To evaluate the utility of our indicators in forecasting if users will change or stay in a community, an articulated experiment has been carried out. First, let us assume that the users usually change their mind when they decide to stay or leave their community over time. Before delving into the evaluation of prediction, we first analysed the VCS distribution of users within communities over three time frames, let us remind the reader that the VCS indicator allows the analysis of user preferences and consumption patterns over time. Then, user decision prediction is carried out to evaluate how much the indicators can be good at discovering changes in user community membership.

Video consumption analysis. Let us focus on the complex relationship that holds between VCS and community membership for both users who stay and leave communities. This relationship will show that if user community membership can be accurately predicted, it will inevitably enable us to accurately predict their watching behaviors. With this purpose, VCS (see Equation 4) are used to gain more detailed insights into how people in these groups interact with the content. In detail, firstly users have been divided into two groups: the first one represents users who continuously stay within their communities throughout three time frames, while the second group represents users who belonged to one cluster in 2016 but switched to the opposite cluster in 2018.

VCS for users who stayed in the same community are shown in Figure 6[A-B]. Let us notice that the consumption scores of users are highly related to the dominant characteristics of their respective communities, as it has been assessed at the community level in Section 4.2. Let us also observe that the graph narrows over time for Cluster 0, indicating a greater concentration of users who prefer videos with ratings between 0 and 0.1. A similar pattern can be observed for Cluster 1, but it eventually converges to 1, suggesting a higher connection with alt-right content. This observed pattern suggests that people consume a greater share of information closely related to their communities over time.

For what concerns users changing community over time, scores are reported in Figure 6[C-D]. let us observe that users shifting from Cluster 0 in 2016 to Cluster 1 in 2018 have an initial habit of only consuming alt-lite videos in 2016. Their content preferences grew in 2017 to include both alt-lite and alt-right videos. However, by 2018, this group has increased their consumption of alt-right videos. In the same context, users who switched from Cluster 1 to 0 started to consume alt-right videos in 2016. By 2018, their content choices will shift toward a focused consumption of alt-lite videos. The observed shift in both groups indicates a distinct change in the content preferences, providing significant insights into the content-consuming behaviors of both the communities. This shift exemplifies the dynamic nature of user preferences, meaning that content consumption habits will change significantly as users move between clusters.

User behavior prediction evaluation. To test the predictive capabilities of the proposed indicators in detecting community membership changes, the deep neural network-based model introduced in Section 3.6 has been evaluated on three distinct sets of input, including: 1) only user comments, 2) comments and the proposed indicators, 3) only the indicators. To prepare the dataset for this experiment the instances were labelled as either "stay" if a user remained within the same community across three consecutive time frames, or "moving" if the user's community membership changed between the first and third time frames. The dataset has been divided into three subsets: training, testing, and evaluation, with proportions of 70%, 15%, and 15% respectively. The results are shown in Table 4 reporting performance metrics scores on the three sets of input. The resulting model achieves an accuracy around 86%, when considering the indicators as inputs. In comparison to 63% when using simple comments or a mix of comments and indicators (68% accuracy). These test results underlie that employing the selected indicators strengthens the effectiveness of community membership change predictors.

	Comment	**Comment + Indicators**	**Indicators**
Accuracy	0.63	0.68	0.86
F1_Score	0.58	0.64	0.85
Recall	0.63	0.68	0.86
Precision	0.59	0.67	0.86

Table 4. Model Performance results for user behavior classification Task into staying and leaving

5 Discussion

The achieved experimental results indicate the capability of users behavior indicators in capturing the evolution of echo chamber over time. Let us state that the first experiment shown in the previous section demonstrates that there is a strong relationship between the proposed indicators with the Echo Chamber Score, which reveal the effective potential of the indicators in describing the temporal evolution of echo chambers, and more in detail how radicalized online communities evolve and reshape themselves over time. These indicators can serve as crucial markers for unveiling important patterns for echo chamber analysis. For instance, an increase in community similarity and closeness within a group suggests a strengthening of ideological connections and content homogeneity, which increases the echo chamber effect.

Moreover, let us remark that the community membership analysis in the second experiment offers a clear evidence of how changes in videos consumption affect user attitudes. In particular, users who stay within the same community tend to watch more videos that resonate with the prevailing ideas of their community, implying a strong affinity for aligned contents. On the other hand, those who choose to switch communities shift their video consumption towards contents that contradict the beliefs of their previous community, demonstrating an attempt to examine a diverse perspective. In addition to that, the combination of this analysis with the predictive model offers a clear advantage for interpreting user movements within echo chamber environments. As shown in the experiments, the relationship indicates that by accurately predicting when users change community, we can effectively forecast their content watching preferences.

In a nutshell, the combination of user language similarity, closeness, and content consumption measurements provides a full picture of the echo chamber dynamics and help predicting user change of community and content to consume within such a state. Therefore, embedding these indicators can serve both an online proactive echo chamber monitoring and future evolution of echo chambers for supporting tasks to moderate such phenomena.

6 Conclusion

This study proposed four indicators to help capturing the complex dynamics of user activity and engagement in different communities on video-sharing social networks. The achieved results show a positive connection between the proposed indicators and a state-of-the-art echo chamber score, demonstrating the efficacy of our technique in understanding the intricacies of echo chamber dynamics over time. Furthermore, the paper explored user behaviors during transitions across communities. In this regard, the approach included a deep neural network model to predict user movements in between communities, emphasizing the effectiveness of the given indicators as useful features for this prediction. In conclusion, the research underlines the importance of these indicators for the evaluation of echo chambers and offers useful insights into the processes of online radicalization and polarization.

Acknowledgement

This work was partially supported by project SERICS (PE00000014) under the MUR National Recovery and Resilience Plan funded by the European Union - NextGenerationEU.

References

1. Alatawi, F., Sheth, P., Liu, H.: Quantifying the echo chamber effect: An embedding distance-based approach. In: Proceedings of the 2023 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. p. 38–45. ASONAM '23, Association for Computing Machinery, New York, NY, USA (2024). https://doi.org/10.1145/3625007.3627731, https://doi.org/10.1145/3625007.3627731
2. Blanca, M.J., Arnau, J., López-Montiel, D., Bono, R., Bendayan, R.: Skewness and kurtosis in real data samples. Methodology (2013)
3. Celikoglu, A., Tirnakli, U.: Skewness and kurtosis analysis for non-gaussian distributions. Physica A: Statistical Mechanics and its Applications **499**, 325–334 (2018)

4. Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., Starnini, M.: The echo chamber effect on social media. Proceedings of the National Academy of Sciences **118**(9), e2023301118 (2021)
5. Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018)
6. Diaz Ruiz, C., Nilsson, T.: Disinformation and echo chambers: how disinformation circulates on social media through identity-driven controversies. Journal of Public Policy & Marketing **42**(1), 18–35 (2023)
7. Gao, Y., Liu, F., Gao, L.: Echo chamber effects on short video platforms. Scientific Reports **13**(1), 6282 (2023)
8. Grusauskaite, K., Carbone, L., Harambam, J., Aupers, S.: Debating (in) echo chambers: How culture shapes communication in conspiracy theory networks on youtube. New Media & Society **0**(0), 14614448231162585 (0). https://doi.org/10.1177/14614448231162585
9. Hamilton, W., Ying, Z., Leskovec, J.: Inductive representation learning on large graphs. Advances in neural information processing systems **30** (2017)
10. Hosseinmardi, H., Ghasemian, A., Clauset, A., Rothschild, D.M., Mobius, M., Watts, D.J.: Evaluating the scale, growth, and origins of right-wing echo chambers on youtube. arXiv preprint arXiv:2011.12843 (2020)
11. Interian, R., G. Marzo, R., Mendoza, I., Ribeiro, C.C.: Network polarization, filter bubbles, and echo chambers: an annotated review of measures and reduction methods. International Transactions in Operational Research **30**(6), 3122–3158 (Oct 2022). https://doi.org/10.1111/itor.13224
12. Jagtap, R., Kumar, A., Goel, R., Sharma, S., Sharma, R., George, C.P.: Misinformation detection on youtube using video captions (2021)
13. Kirdemir, B., Kready, J., Mead, E., Hussain, M.N., Agarwal, N.: Examining video recommendation bias on youtube. In: Boratto, L., Faralli, S., Marras, M., Stilo, G. (eds.) Advances in Bias and Fairness in Information Retrieval. pp. 106–116. Springer International Publishing, Cham (2021)
14. Kratzke, N.: How to find orchestrated trolls? a case study on identifying polarized twitter echo chambers. Computers **12**(3), 57 (2023)
15. La Cava, L., Aiello, L., Tagarelli, A.: Drivers of social influence in the twitter migration to mastodon. Scientific Reports **13** (12 2023). https://doi.org/10.1038/s41598-023-48200-7
16. Lutz, M., Gadaginmath, S., Vairavan, N., Mui, P.: Examining political bias within youtube search and recommendation algorithms. In: 2021 IEEE Symposium Series on Computational Intelligence (SSCI). pp. 1–7 (Dec 2021). https://doi.org/10.1109/SSCI50451.2021.9660012
17. Marco, N.D., Cinelli, M., Quattrociocchi, W.: Infodemics on youtube: Reliability of content and echo chambers on covid-19. ArXiv **abs/2106.08684** (2021)
18. McDonald, J.B., Sorensen, J., Turley, P.A.: Skewness and kurtosis properties of income distribution models. Review of Income and Wealth **59**(2), 360–374 (2013)
19. Ribeiro, M.H., Ottoni, R., West, R., Almeida, V.A., Meira Jr, W.: Auditing radicalization pathways on youtube. In: Proceedings of the 2020 conference on fairness, accountability, and transparency. pp. 131–141 (2020)
20. Sun, M., Ma, X., Huo, Y.: Does social media usersrsquo; interaction influence the formation of echo chambers? social network analysis based on vaccine video comments on youtube. International Journal of Environmental Research and Public Health **19**(23) (2022). https://doi.org/10.3390/ijerph192315869