Evaluating Structural Attractors and Retainers in YouTube Recommendation Networks

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Abstract. Recommendation systems, while designed to personalize user experiences, can sometimes lead to recommendation traps, which are structurally embedded areas within a recommendation network that draw users in and keep them entrapped longer than intended. One such system is YouTube's recommendation engine, which not only plays a central role in shaping content consumption [1] but also raises concerns about algorithmic entrapment and prolonged user retention. In this study, we leverage network-based frameworks to detect and analyze recommendation traps within YouTube's recommendation network. Focusing primarily on three contexts: viz., the China–Uyghur discourse, the Cheng Ho propaganda, and the 2024 Trump assassination attempt, we apply Focal Structure Analysis (FSA) to extract dense, high-impact subgraphs. These focal structures are then compared with equal-sized groups constructed from top-ranked nodes through different centrality measures (i.e., degree, betweenness, closeness, and eigenvector). To evaluate the impact of recommendation traps, we introduce two structural metrics: *attraction* - which captures how quickly these structures are reached from nodes outside the group, and *retention* - which measures how long the traversal remains within the structure once entered. Simulated random walks revealed that focal structures consistently outperformed baseline groups, particularly in the retention metric, suggesting focal structures' effectiveness in identifying recommendation traps. These findings further emphasize the role of network structural cohesion in shaping user pathways and offer a scalable method for identifying entrapment zones in algorithmic systems.

Keywords: Random Walk, Attractors, Retainers, YouTube, Recommendation Network, Social Network Analysis

1 Introduction

Recommendation systems have become foundational components of digital platforms, guiding user exposure, engagement, and navigation across vast content spaces. While these systems are optimized to personalize user experience, they can also give rise to recommendation traps, structurally embedded zones within a recommendation graph that repeatedly draw users in and keep them engaged longer than expected. These traps emerge not from the content but from how the recommendation network is structurally organized to promote recursive navigation within tightly interconnected regions.

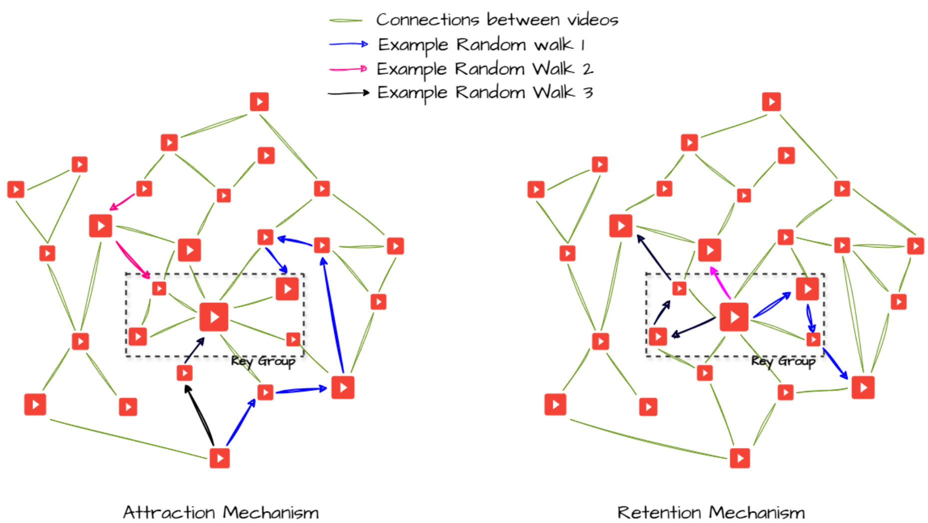


Fig. 1. Visualization of the attraction and retention mechanisms in a YouTube recommendation network. The left panel illustrates the attraction mechanism, where random walks (blue, pink, and black arrows) highlight the paths leading users toward a key group of videos. The right side displays the retention mechanism, with random walks illustrating the paths users take to remain within a group of related videos, emphasizing the sustained engagement within that group. The dashed boxes represent the key group entity that attracts or retains users.

YouTube's recommendation engine exemplifies this phenomenon, shaping most user watch time through algorithmically generated video suggestions [1]. Prior research has raised concerns about echo chambers, algorithmic bias, and overexposure to homogeneous content [12], but the structural mechanisms through which users become entrapped in recommendation cycles remain underexplored. Most existing studies focus on content themes, topical polarization, engagement metrics [16] or the role of semiotics in shaping thematically aligned exposure patterns [17],[7], leaving a gap in understanding the purely structural underpinnings of how long users stay within a part of the network and how hard it is to leave once they enter.

In this work, we take a network-centric approach [9] to analyzing recommendation traps, focusing on the structural dynamics of attraction and retention. We define attraction as the likelihood that a user, modeled as a random walker, enters a given subgraph from the broader network, and retention as the extent to which that subgraph sustains traversal once entered, as illustrated in the demonstration shown in Figure 1. These two metrics provide a behavioral lens through which to assess the influence of key network regions independent of content or user preferences.

To identify structurally meaningful zones within the YouTube recommendation network, we apply Focal Structure Analysis (FSA), a social network analysis method, to detect small, densely connected node sets with strong collective influence. We then extract the key focal structures in each network and compare their behavior against equal-sized groups derived from traditional centrality measures. After that, we simulate random walks over three real-world YouTube recommendation networks, capturing interaction dynamics within socio-political contexts: the China–Uyghur, the Cheng Ho, and the 2024 Trump assassination attempt. Thus, we aim to address the following research questions to better understand the structural dynamics of attraction and retention within YouTube recommendation networks.

- **RQ1:** Do focal structures exhibit stronger attraction than groups derived from traditional centrality measures?
- **RQ2:** Are focal structures more effective at retaining traversal within recommendation networks, indicating a greater structural capacity for user entrapment?

Our results show that focal structures consistently outperform centrality-based groups in attraction and retention, revealing their potential role as structural attractors and retainers. These findings indicate that certain regions within a recommendation network can concentrate user attention primarily due to their structural configuration rather than the specific content they present.

Overall, this work contributes a scalable and interpretable framework for identifying recommendation traps through structural analysis. By simulating user flow with random walks and isolating structural features that sustain or redirect attention, we offer platform designers, researchers, and policymakers a novel toolset for diagnosing and intervening in algorithmic engagement patterns without relying heavily on content-based inference.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature on recommendation and network-based influence analysis. Section 3 outlines our methodology, including focal structure analysis, simulation design for attraction and retention. Section 4 presents experimental results on attraction and retention dynamics across datasets. Finally, Section 5 concludes with a discussion on the implications of our findings and directions for future research.

2 Literature Review

This section reviews prior work related to two central themes of our study: (1) identifying influential sets of entities in social networks, and (2) applying random walk-based techniques in network analysis, particularly for understanding behavioral flow, and structural influence in recommendation systems.

2.1 Identifying Sets of Key Social Network Entities

Identifying a network's most structurally influential nodes or node groups is foundational in social network analysis. Numerous approaches have been developed to uncover such key entities. Traditional techniques like HITS (Hyperlink-Induced Topic Search) [22] and PageRank [11] provide node-level importance scores based on connectivity, authority, and recursive influence. While these methods have proven effective in highlighting influential individuals, community detection methods aim to uncover clusters of similar or densely interconnected nodes. Communities are typically defined by higher intra-group edge densities than inter-group connections, revealing thematic or structural cohesion [6].

Going beyond individual influence and broad community detection, researchers have explored the identification of smaller, structurally cohesive subgroups that exhibit disproportionate influence, often referred to as focal structures. For instance, Sen et al. [25] applied the Louvain method for modularity maximization [10] to detect such focal groups in social and biological networks. These smaller, targeted structures yielded more actionable insights than broader community partitions. Follow-up work showed how these structures could be refined by merging candidate subgraphs with similar topological patterns, enabling the detection of dense cliques and sparse, strategically connected groups [24].

Building on these methods, Alassad et al. [2] introduced a hybrid model that combines node-level centrality with group-level modularity. Their bi-level maximization framework addressed limitations in earlier focal structure methods by balancing local importance with global structure, thereby improving the extraction of influential sets in complex networks.

2.2 Random Walks in Network Analysis

Random walk algorithms are critical tools in network analysis that excel at identifying influential nodes, anomaly detection, and optimizing recommendation systems, particularly in large-scale and complex networks. Previous researchers [26] employed biased random walks to differentiate between key and ordinary nodes in social networks effectively, outperforming traditional methods like PageRank, which is crucial for viral marketing applications. Similarly, Huang et al. [20] improved academic collaboration recommendations by utilizing random walks with restart and integrating multi-similarity features for enhanced prediction accuracy. Zhou et al. [27] introduced MTO-Sampling, which dynamically rewires network topology to accelerate random walk convergence, thereby increasing efficiency in data-restricted environments. In link prediction, researchers [5] combined network structure and node attributes to enhance the accuracy of future link predictions beyond unsupervised methods. Additionally, Jia et al. [21] developed SybilWalk for fake account detection, demonstrating improved accuracy and robustness in weak-homophily networks like Twitter. Furthermore, random walks are also pivotal in personalized recommendations. Alessandretti et al. [4] examined the effects of user activity and attractiveness, yielding insights into information flow in dynamic networks. Whereas another researcher [15] created a random walk model that enhances recommendation accuracy and diversity compared to traditional approaches. The continual advancements in random walk algorithms highlight their expanding application across various fields, including social network analysis, personalized recommendations, and fraud detection, pointing toward future innovations in network analysis methodologies.

Despite the extensive use of random walk algorithms in social network analysis, their application to studying recommendation networks remains underexplored in the context of structural attractors and retainers to the best of our knowledge. Existing studies primarily focus on content-driven [8] or centrality-based methods to understand user engagement, with recent work also examining how metadata and GPT-based narrative extraction reveal latent structures in YouTube recommendation networks [18]. This work introduces a novel approach by applying random walk simulations to uncover how structural properties, such as attraction and retention dynamics, influence user behavior within recommendation networks. Using random walks to model user flow, we fill a critical gap in the literature, offering a new lens to understand how recommendation systems shape long-term engagement purely through network topology.

3 Methodology

This section presents a comprehensive methodology for identifying and analyzing structural attractors and retainers within YouTube recommendation networks. We first begin with a detailed explanation of the data collection process, including the contextual background of the datasets and the construction of recommendation graphs. We then present the eigenvector centrality approach to rank the key focal structure. In addition, we lay out the foundation for analyzing attraction and retention using random walks. Lastly, this section explores two metrics, attraction and retention factors, which help us quantify how effectively network structural groups capture key behavioral patterns in the YouTube recommendation network.

3.1 Data Collection

The data collection process in this study was designed to systematically capture YouTube's algorithmic behavior through its 'watch-next' recommendations. We analyzed three distinct contexts: the China–Uyghur discourse, the Cheng Ho propaganda, and the 2024 Trump assassination attempt datasets. Below, we provide brief background details for these three contexts and the motivation for studying them.

China-Uyghur Discourse - The conflict in Xinjiang centers on the challenges faced by the Uyghur Muslim minority in China, which includes issues such as cultural suppression, ethnic tensions, and government policies [13]. Researchers have examined this situation through various lenses, including identity politics, language policies, and the dynamics between majority and minority groups, as well as the desire for self-governance [19]. The international response between 2018 and 2022 has drawn increased attention to human rights issues, highlighting the severity of the conflict.

Context	Keywords and/or Hashtags
China–Uyghur Discourse	
	Penindasan / oppression + Uighur / Uyghur, Kejam / cruel + Uighur / Uyghur, “China is Terrorist”, “Stop Genocide”, “Save Muslim Uyghur”, “Peduli Uyghur” / “Care Uyghur”, Hizbul Tahrir / HTI + Uighur / Uyghur, Front Pembela Islam / FPI + Uighur / Uyghur, Nahdlatul Ulama + Uighur / Uyghur, Pendidikan / education + Uighur / Uyghur, Xiao Qian + Uighur / Uyghur
Cheng Ho Propaganda	
	Cheng Ho, Zheng He, Sam Po Kong, Sam Poo Kong, Daerah Otonom Uighur Singkiang, Singkiang, Hatta + 1957, Novi Basuki, Sam Po Bo, Cheng Ho / “Zheng He” + laksamana + damai, Sam Po Kong + Islam + Indonesia, 1421 Saat China Menemukan Dunia + “Gavin Menzies”, Gavin Menzies, Cheng Ho / “Zheng He” “Columbus”
2024 Trump Assassination Attempt	
	#TrumpAssassinationAttempt, #DeepStateConspiracy, #GodSaveTrump, #TrumpSurvives, #StagedAssassination, #TrumpInDanger, #TrumpEndgame, #AssassinateTrump, “Joe Biden sent the orders”, “Trump assassination cover-up”, “Trump death hoax”, “Trump secret plot”,

Table 1. The list of keywords and/or hashtags used for data collection across the three case studies.

Cheng Ho Propaganda - In contemporary discourse, the Chinese Communist Party (CCP) has reinterpreted the story of the 15th-century admiral Zheng He, also known as Cheng Ho, to bolster its current political messages. Once celebrated for his peaceful sea voyages, Zheng He is now portrayed as a symbol of religious tolerance and diplomacy [14]. This shift aligns with China’s efforts to address criticism regarding its treatment of Uyghur Muslims and to promote its Maritime Silk Road initiative. The CCP aims to enhance its soft power by rebranding this historical figure, particularly in Southeast Asia.

Trump Assassination Attempt - On July 13, 2024, former President Donald Trump survived an assassination attempt during a campaign rally in Butler, Pennsylvania [23]. The shooter, a 20-year-old Thomas Matthew Crooks, grazed Trump’s ear with a bullet and fatally shot a nearby bystander, Corey Comperatore. The incident sparked widespread concern over security failures, which led to the resignation of the Secret Service director [3]. A photo of a bloodied Trump raising his fist went viral, which symbolized resilience and reportedly boosted his support.

We selected the China–Uyghur discourse, the Cheng Ho propaganda, and the 2024 Trump assassination attempt datasets due to their geopolitical, ideological, and sociopolitical relevance. These cases offer distinct yet complementary contexts, which in turn examine how YouTube's recommendation algorithm amplifies sensitive content and shapes user exposure through the structural properties of its recommendation network.

After selecting the datasets based on their geopolitical and sociopolitical significance, we then collected relevant video data from YouTube. To initiate data collection, we conducted workshops with subject matter experts to develop targeted keyword lists related to the China–Uyghur discourse, the Cheng Ho propaganda, and the 2024 Trump assassination attempt datasets. These curated keywords were used as search queries on YouTube to retrieve an initial set of seed videos. While the number of keywords varies across the three datasets (as shown in Table 1), this variation does not compromise the validity or comparability of our analysis, as the subsequent network construction is based on recommendation relationships rather than keyword frequency alone.

3.2 Network Construction

The China–Uyghur discourse, the Cheng Ho propaganda, and the 2024 Trump assassination attempt datasets consisted of 9,748, 8,489, and 5,553 videos and 14,307, 13,384, and 9,689 interactions, respectively. These interactions represented YouTube's recommendation paths across several hops, and they were used to start the network construction process. The initial networks had an average clustering coefficient of 0.067, 0.062, and 0.074, respectively, suggesting comparatively sparse and loosely connected network structures. However, the resulting graphs are not just simple tree-like structures expanding outward from seed videos; rather, they exhibit cyclical connections, where later recommendations frequently link back to previously recommended nodes. This recursive connectivity leads to a more structurally integrated network by making the network less dependent on the direction of the initial crawl depicted in Figure 2.

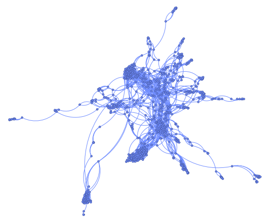
3.3 Focal Structure Analysis

Focal Structure Analysis (FSA) is a network-based optimization framework designed to detect key groups of users, primarily known as the focal structures. These network structures collectively exert significant influence within a social network. Unlike individual centrality-based measures or community detection methods, FSA identifies minimal yet highly impactful groups by solving a decomposition-based optimization problem over the unimodal user-user graph.

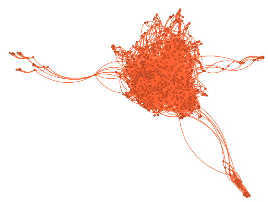
Let $G = (V, E)$ represent a social network, where V is the set of users (nodes) and E the set of interactions (edges). The objective is to identify a subset $S \subseteq V$ such that the collective influence of S, measured by an aggregate centrality function, is maximized under structural constraints:

$$\max_{S \subseteq V,\, |S| \leq k} \sum_{i \in S} C(i) \tag{1}$$

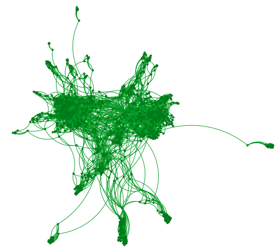
where:



(a) The China-Uyghur Discourse YouTube Recommendation Network



(b) The Cheng Ho Propaganda YouTube Recommendation Network



(c)2024 Trump Assassination Attempt Recommendation Network

Fig. 2. Visualizations of the YouTube recommendation networks constructed for the (a) China–Uyghur discourse, (b) the Cheng Ho propaganda, and (c) the 2024 Trump assassination attempt. Despite being seeded through outward crawls, each network exhibits significant interconnectivity and cyclic paths, forming structurally integrated graphs rather than simple tree-like expansions.

– $C(i)$ is the centrality score of node i (e.g., degree, closeness, or betweenness),
– k is a tunable parameter representing the maximum allowed group size.

This combinatorial problem is solved using a decomposition-based optimization strategy (i.e., FSA), which iteratively partitions the network and refines candidate sets using modularity and intra-connectivity heuristics. To ensure the internal cohesion of each focal structure, we enforce a minimum density constraint:

$$\delta(S) = \frac{2|E_S|}{|S|(|S|-1)} \geq \tau \tag{2}$$

where E_S is the set of edges within S, and $\tau \in [0,1]$ is a predefined density threshold.

By maximizing Equation 1 subject to the constraint in Equation 2, FSA yields focal structures characterized by both high influence and dense internal connectivity. These structures are ideal for analyzing structural influence in social networks, particularly in scenarios involving information flow, behavioral coordination, or structural intervention.

3.4 Centrality-Based Group Construction

To ensure comparability, we controlled for group size by selecting the same number of nodes across the key focal structure and centrality-based groups. Specifically, we formed four separate centrality-based groups by selecting the top-k ranked nodes for each centrality measure, namely Betweenness, Closeness, Degree, and Eigenvector, where k corresponds to the size of the top focal structure. For each ranking method, we extracted the induced subgraph formed by these top-k nodes, preserving their structural relationships. This approach ensures consistent group size across all methods, allowing us to assess how different structural configurations influence attraction and retention dynamics.

While this does not fully eliminate differences in connectivity or dispersion, it provides a consistent evaluation setting to assess how group-level versus node-level strategies influence structural performance. Importantly, we treat these centrality-based selections as induced subgraphs, enabling us to isolate the effect of internal connectivity in shaping attraction and retention outcomes.

3.5 Attraction and Retention Analysis via Random Walks

We implement two complementary random walk-based simulations to evaluate the behavioral influence of the network structures within recommendation networks. One measures attraction, and the other measures retention. The attraction analysis (Algorithm 1) quantifies how easily random walkers originating outside the network structures arrive at them, capturing their pull or accessibility. In contrast, the retention analysis (Algorithm 2) measures how long random walkers remain within the network structures before exiting, reflecting the ability of these subgraphs to sustain traversal. Both procedures are repeated multiple times across the network to compute average metrics and assess the structural influence of focal structures compared to centrality-based groups.

Algorithm 1 Attraction Analysis via Random Walks

Require: Recommendation network $G(V, E)$
Require: Focal structures $FS = \{FS_1, FS_2, ..., FS_n\}$, walk length L, iterations N
Ensure: Average hops to reach focal structures, frequency of landings

Extract non-focal structure nodes: $S = V \setminus \bigcup FS$
for each node $s \in S$ **do**
    for each iteration $i = 1$ to N **do**
        Initialize current node $u \leftarrow s$
        Set hop count $h \leftarrow 0$
        while $h < L$ **do**
            Select a random neighbor v of u
            Move to v, update $u \leftarrow v$
            Increment hop count: $h \leftarrow h + 1$
            if $v \in FS_j$ for any j **then**
                Record landing in FS_j and hops taken
                Break
            end if
        end while
    end for
end for
Compute average attraction hops for each focal structure

Lastly, to evaluate the behavioral significance of focal structures compared to centrality-based groups, we compute two metrics: Retention and Attraction

Factor as defined in equations 3 and 4 respectively. These ratios compare the average number of hops for user retention and attraction in traditional centrality-based groups versus those in the top focal structure. Values less than 1 indicate that the focal structure exhibits stronger user retention or attraction compared to centrality-based groups, validating its behavioral prominence in the recommendation network.

$$\text{Attraction Factor} = \frac{\text{Mean Attraction Hops}_{\text{Central Groups}}}{\text{Mean Attraction Hops}_{\text{Focal Structure}}} \tag{3}$$

Algorithm 2 Retention Analysis via Random Walks

Require: Recommendation network $G(V, E)$
Require: Focal structures $FS = \{FS_1, FS_2, ..., FS_n\}$, walk length L, iterations N
Ensure: Average hops to exit focal structures

for each focal structure $FS_j \in FS$ **do**
  for each node $s \in FS_j$ **do**
    for each iteration $i = 1$ to N **do**
      Initialize current node $u \leftarrow s$
      Set hop count $h \leftarrow 0$
      while $h < L$ **do**
        Select a random neighbor v of u
        Move to v, update $u \leftarrow v$
        Increment hop count: $h \leftarrow h + 1$
        if $v \notin FS_j$ **then**
          Record exit and hops taken
          Break
        end if
      end while
    end for
  end for
end for
Compute average retention hops for each focal structure

$$\text{Retention Factor} = \frac{\text{Mean Retention Hops}_{\text{Central Groups}}}{\text{Mean Retention Hops}_{\text{Focal Structure}}} \tag{4}$$

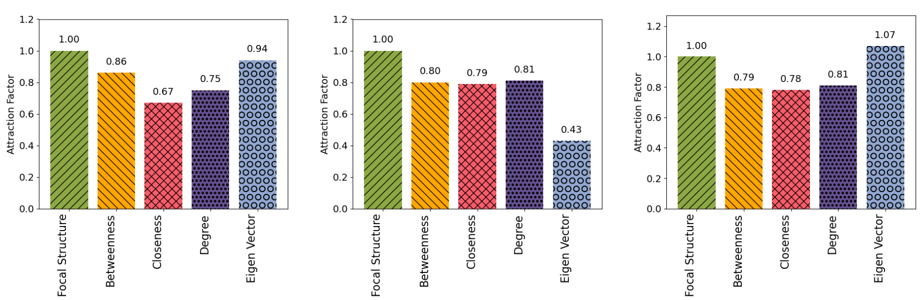
4 Experimental Results and Analysis

In this study, we analyze two complementary properties, attraction and retention, to evaluate how different network-based strategies identify node sets that are more likely to pull or retain interaction within recommendation networks. While attraction refers to the capacity to draw users into a subset of videos, retention reflects how effectively a subset of videos sustains continued user traversal within that specific subset of videos once the entry occurs. These structural dynamics serve as proxies for entry and persistence within influential regions of a graph.

We conduct experiments across three distinct YouTube recommendation network datasets. We then apply five social network analysis (SNA) approaches, including Focal Structure Analysis (FSA), Betweenness Centrality, Closeness Centrality, Degree Centrality, and Eigenvector Centrality. This approach allows us to evaluate the structural effectiveness of node sets identified by different SNA strategies under a fixed group-size constraint. We use the top focal structure as a reference for group size since it allows consistent and size-controlled comparison across all methods. This ensures that each method is evaluated under the same conditions, using the same number of top-ranked nodes. Comparing other methods against this benchmark enables us to assess whether individual node-based rankings can replicate or approximate the structural advantages captured by group-based focal structures.

4.1 Attraction Dynamics

Attraction analysis on the Focal Structure Analysis consistently outperforms all other methods in two network settings. This suggests that structurally cohesive subgraphs identified via FSA are particularly well-positioned to intercept paths or flows within the network. While centrality-based approaches, particularly degree, and betweenness, show competitive attraction performance, their effectiveness appears more sensitive to network-specific topologies, especially in cases where influence is concentrated in central bridging nodes or hubs.



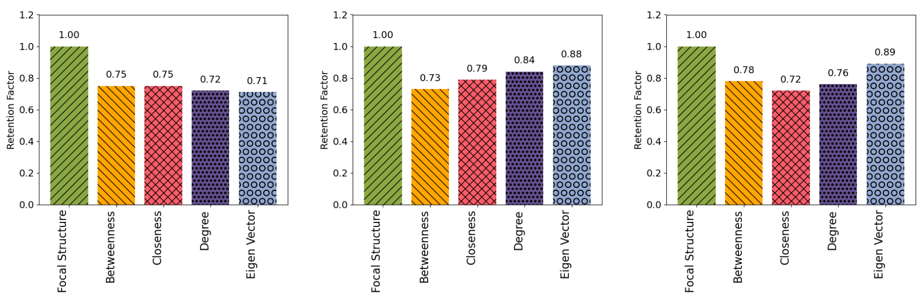
(a) China–Uyghur (b) Cheng Ho (c) Trump Assassination

Fig. 3. Attraction Dynamics Across Three YouTube Recommendation Networks: (a) China–Uyghur, (b) Cheng Ho, and (c) 2024 Trump Assassination Attempt. Focal structure values are normalized to 1, allowing for direct comparisons across other centrality-based group values represented relative to this baseline.

Eigenvector centrality, in contrast, exhibits inconsistent attraction performance, likely due to its reliance on global importance, which does not always align with localized structural pull. These findings indicate that the ability to attract is not solely a function of node prominence but also of how densely and locally a set of nodes is embedded in the broader network structure, as depicted in Figure 3 and thus addressing our research question **RQ1**.

4.2 Retention Dynamics

Retention analysis reveals a more decisive and consistent outcome: Focal Structure Analysis outperforms all baseline methods across all three datasets. Regardless of the network's size or connectivity pattern, the subgraphs identified by FSA demonstrate a greater ability to sustain internal flow and user traversal once entered. This suggests that focal structures possess an internal cohesion that facilitates continued interaction, likely due to their high intra-connectivity and structural redundancy.



(a) China–Uyghur (b) Cheng Ho (c) Trump Assassination

Fig. 4. Retention Dynamics Across Three YouTube Recommendation Networks: (a) China–Uyghur, (b) Cheng Ho, and (c) 2024 Trump Assassination Attempt. Focal structure values are normalized to 1, allowing for direct comparisons across other centrality-based group values represented relative to this baseline.

In contrast, centrality-based approaches exhibit variable retention characteristics. Betweenness and closeness centralities, which emphasize shortest paths and intermediary roles, often fail to preserve flow once initiated, likely because they highlight transient rather than persistent structures. Even eigenvector centrality, despite improved retention over attraction in some cases, fails to match the retention strength exhibited by FSA consistently, as shown in Figure 4 and thereby addressing our research question **RQ2**.

5 Conclusion and Future Work

This study introduced a structural approach to detecting recommendation traps in YouTube's recommendation network by analyzing attraction and retention dynamics. Using Focal Structure Analysis (FSA), we identified dense subgraphs that consistently outperformed centrality-based groups, especially in retention, highlighting their ability to sustain user traversal based on structure alone. We demonstrated through random walk simulations on three sociopolitical datasets, such as the China–Uyghur discourse, the Cheng Ho propaganda, and the 2024 Trump assassination attempt, that FSA-derived structures consistently outperform traditional centrality-based groups, particularly in retention. This finding highlights the importance of internal cohesion in sustaining user traversal independent of content.

Our work underscores the value of topology-driven diagnostics in understanding how algorithmic systems concentrate and sustain user attention, independent of content. This has important implications for understanding how recommendation systems guide engagement, highlighting the need for interventions that address structural dynamics and not just content moderation.

In future work, we plan to investigate the impact of node proximity on attraction and retention by simulating random walks originating from varying distances, including one-hop and two-hop neighbors and beyond, relative to the structural groups. Additionally, we will evaluate the rate at which walks initiated from within these groups can reach nodes located at increasing distances. This hop-based analysis aims to provide a deeper understanding of the structural reach and containment characteristics of different regions within the network.

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