



## MORAL DISCOURSE AND NETWORK FRAGMENTATION IN YOUTUBE COMMENTS

## DISKURSUS MORAL DAN FRAGMENTASI JARINGAN DALAM KOMENTAR YOUTUBE

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### ***ABSTRACT***

This study analyzes moral reasoning and fragmented discourse in YouTube comments on a viral Indonesian sexual violence involving a religious figure. Using Mixed Methods Social Network Analysis on 6,018 comments from 5,484 users, results reveal a sparse, fragmented network with low interaction but mostly neutral sentiment (76.9%) and limited emotional polarization. Six thematic clusters emerge as affective micro-publics, expressing diverse responses such as moral-religious condemnation, emotional support, social reflection, stigma, activism, and ethical critique, showing the discussion is divided into value-aligned enclaves rather than a unified deliberative space.

**Keywords:** *moral reasoning; social network analysis (SNA); discourse fragmentation*

### ***ABSTRAK***

Penelitian ini menganalisis penalaran moral dan diskursus yang terfragmentasi dalam komentar YouTube terkait kasus kekerasan seksual viral di Indonesia yang melibatkan seorang tokoh agama. Dengan menggunakan Mixed Methods Social Network Analysis pada 6.018 komentar dari 5.484 pengguna, hasil penelitian mengungkapkan jaringan yang jarang dan terfragmentasi dengan interaksi yang rendah namun didominasi oleh sentimen netral (76,9%) serta polarisasi emosional yang terbatas. Enam kluster tematik muncul sebagai mikro-publik afektif, yang mengekspresikan respons beragam seperti kecaman moral-religius, dukungan emosional, refleksi sosial, stigma, aktivisme, dan kritik etis, menunjukkan bahwa diskusi terbagi ke dalam kelompok yang selaras nilai daripada ruang deliberatif yang terpadu.

**Kata kunci:** *penalaran moral; analisis jejaring sosial (SNA); fragmentasi wacana*

## **INTRODUCTION**

YouTube serves as a key platform for shaping public opinion on sensitive moral issues, especially in religious societies like Indonesia, where it is the most popular social media ((Rahma Dinti et al., 2024). As an “affective discursive space” (Papacharissi, 2015)), YouTube comments reflect how users negotiate moral claims and express emotions in controversies involving religious authority. Features like algorithmic amplification and visible engagement foster value-based micro-communities and echo chambers, leading to “affective fragmentation,” where moral-emotional publics coexist with little cross-group interaction, deepening ideological and emotional divides (Cinelli et al., 2021; Törnberg, 2018).

While Social Network Analysis (SNA) effectively maps such community structures and interactions (Fenton & Procter, 2019; Himelboim et al., 2017; Isa & Himelboim, 2018), most research focuses on Western political polarization, neglecting the role of moral and religious norms in non-Western digital publics. This study addresses this gap by examining fragmented affective publics and emotional polarization in YouTube comments on a viral Indonesian sexual violence case involving a religious leader, using Mixed Methods Social Network Analysis (MMSNA) to better understand online moral discourse in socio-religious contexts.

Specifically, this study aims to (1) map the distribution and connectivity of communities within the comment network, (2) identify structural inequalities and key discursive clusters, and (3) analyze patterns of emotional polarization among these communities using a Mixed Methods Social Network Analysis (MMSNA) approach. By doing so, this research contributes to a more nuanced understanding of how digital affective publics form and fragment around issues of morality and authority in a non-Western socio-religious context.

## **CONCEPTUAL FRAMEWORK**

Recent research highlights the increasing centrality of social media as a space for public meaning-making, especially around moralized and contentious issues. Over the past decade, scholars have examined how platforms like YouTube function not merely

as entertainment spaces but as affective and discursive arenas that shape public deliberation, identity negotiation, and emotional expression (Papacharissi, 2014). In religiously complex societies, these dynamics become even more pronounced, as online discussions about moral controversies intersect with deeply embedded cultural and religious norms.

A substantial body of research has explored how user interactions on social media generate emergent network structures that influence discourse trajectories. Studies show that viral comments and algorithmically amplified interactions often create clustered conversation patterns, leading to echo chambers and polarized discursive enclaves (Cinelli et al., 2021). Other scholars argue that beyond binary polarization, digital publics may exhibit affective fragmentation, where multiple moral-emotional communities coexist with limited cross-group interaction (Törnberg, 2018).

Social Network Analysis (SNA) has become a critical methodological approach for uncovering such dynamics, enabling researchers to quantify community structures, identify influential actors, and reveal patterns of structural inequality in online discourse (Isa & Himelboim, 2018). Over the last ten years, SNA studies have documented the architecture of digital publics across platforms and issues, from political communication to health misinformation and cultural conflicts. However, most of these studies remain centered on Western sociopolitical contexts.

Research examining moral and religious discourse, particularly within non-Western digital environments, remains relatively limited. Scholars note that moral publics in the Global South often operate through different affective logics, authority structures, and cultural frames compared to Western systems. The interplay between religious authority, digital participation, and moral reasoning remains under-theorized, especially in Southeast Asia, where social media serves as a key arena for negotiating religious identity and moral claims.

Within this gap, studies on gendered and sexual violence discourse online have begun to emerge, showing how digital publics respond to moral shocks and how emotions such as anger, empathy, or outrage circulate across networked communities. Yet, very few studies integrate moral-religious contexts, platform-specific affordances,

and networked emotional dynamics in a single analytical framework.

Mixed Methods Social Network Analysis (MMSNA) has recently gained traction as a powerful approach for bridging structural and interpretive perspectives, enabling researchers to link network topology with discursive patterns, emotional content, and cultural meaning-making (Froehlich et al., 2020; Henry et al., 2025; Yu et al., 2023). Over the last decade, MMSNA has been successfully applied to political discourse, activist communities, and polarized online environments, but its application to morally charged religious controversies in Indonesia remains rare.

Taken together, the literature underscores the need for contextually grounded analyses of digital affective publics, particularly in non-Western societies where religious authority and moral discourse play central roles. This study responds to this gap by analyzing community structures, emotional polarization, and discursive clustering in the YouTube comment network surrounding a viral Indonesian video involving sexual violence by a religious authority figure. By combining SNA with qualitative emotional and thematic analysis, this study advances current scholarship on digital moral publics and contributes to a more nuanced understanding of affective fragmentation in socio-religious contexts.

## **METODOLOGY**

This study uses a Mixed Methods Social Network Analysis (MMSNA) combining Social Network Analysis (SNA) and sentiment analysis to explore user interactions (Froehlich et al., 2020), community structures, and fragmentation in YouTube comments on a moral-religious controversy. Data from a viral video were collected via YouTube Data API, anonymized, and pre-processed with text-cleaning steps (Ahuja & Shakeel, 2017; Sirisha et al., 2024).

The interaction network was built with NetworkX and visualized in Gephi. Sentiment classification employed RoBERTa to categorize comments as positive, neutral, or negative (Syukriyansyah & Damayanti, 2025). SNA metrics like modularity, degree centrality, and connected components measured network cohesion and segmentation. Communities were detected using the Louvain algorithm, with

inequality assessed by Gini and skewness. Qualitative analysis of dominant words and comments clarified discursive themes per cluster. Emotional polarization was assessed by combining sentiment data with community structures through proportional sentiment distributions and Mean Sentiment Scores. The study reveals how network connectivity, discourse clustering, and emotional divergence create fragmented digital publics, forming affective enclaves with limited cross-community interaction in Indonesia's online moral discourse.

## FINDING AND DISCUSSION

The data collection process produced 6,018 comments, 5,414 top-level comments and 604 replies, from 5,484 unique users, with slight discrepancies from the publicly displayed YouTube count due to API limitations in retrieving deleted, hidden, or spam-filtered comments. The collected dataset was then used to construct a reply-based interaction network that maps user-to-user exchanges, forming the analytical foundation for both Social Network Analysis (SNA) and sentiment analysis.

Table 1. Distribution of Communicative Activity within the YouTube Comment Space

Category	Count	Description
Total Comments	6018	Total number of comments successfully extracted
Top-Level Comments	5414	Comments posted directly in response to the video
Comment Replies	604	Comments posted in response to another user's comment
Unique Users	5484	Number of distinct user accounts involved in the discussion

Source: Research data, processed by researchers, 2025

Table 1 shows the distribution of communicative activity within the YouTube comment space. The significantly larger number of top-level comments compared to replies indicates a dominance of direct opinion expression in response to the video content, with relatively limited user-to-user interaction. This pattern provides a basis for understanding public participation dynamics prior to the data pre-processing and social network analysis stages.

## 1. Data Pre-processing

Based on the construction using NetworkX, the formed social network consists of 5,484 nodes and 591 edges, as shown in Table 2. The number of nodes represents the total unique users participating in the discussion, while the number of edges depicts actual relationships between users through replies or direct mentions.

Table 2. Basic Statistics of the Youtube Social Network

Parameter	Value	Description
Number of Nodes	5484	Unique users in the discussion
Number of Edges	591	User interactions (replies)

Source: Research data, processed by researchers, 2025

Overall, the results show relatively low interaction among users, indicating a sparse and loosely connected network typical of discussions on sensitive topics where participants share opinions individually rather than engaging in direct dialogue; the pre-processed data was then imported into Gephi for visualization and for computing advanced network metrics, including degree of connectivity, community modularity, and user influence distribution.

Pre-processing was performed on 6,018 comments, results show a structured transformation of raw comments into clean, analyzable text. Case folding converts all text to lowercase, while cleaning removes numbers and emojis. Tokenization then splits comments into individual word units, followed by normalization that replaces slang with standard forms. Stop-word removal eliminates non-essential words, and stemming reduces terms to their root forms. Together, these steps ensure the comment data is consistent, simplified, and ready for computational analysis. The output of this pipeline served as input to the Indonesian RoBERTa-base model for sentiment labeling in the subsequent stage.

Sentiment analysis on 6,018 comments using a fine-tuned RoBERTa-base model (positive, neutral, negative) shows that neutral sentiment overwhelmingly dominates the public discourse, far exceeding both positive and negative categories, with detailed distribution presented in Table 3.

Table 3. Distribution of Youtube Comment Sentiments

Sentiment	Count	Percentage (%)
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Neutral	4792	76.9
Negative	811	13.5
Positive	415	6.9
Total	6018	100

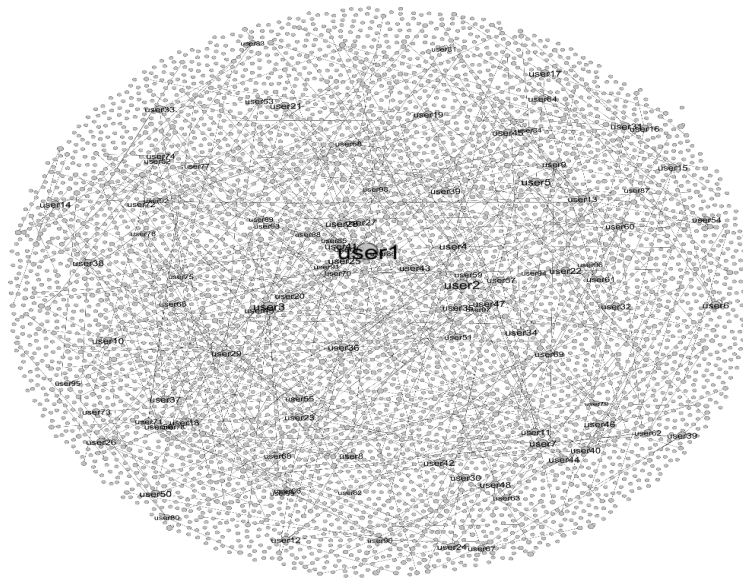
Source: Research data, processed by researchers, 2025

The dominance of neutral sentiment indicates that most users responded to the victim's narrative with emotional caution, focusing on factual descriptions of the event or offering support without aggressive expression. Positive sentiment frequently manifested as empathy, prayers, and solidarity with the victim, while negative sentiment was directed towards the perpetrator and the social systems perceived as negligent.

This tendency reflects that, within the context of sexual violence issues, the digital discourse space on YouTube can function as an arena of affective moderation, where the public expresses moral concern without reinforcing extreme polarization

Network topology analysis was conducted to understand the distribution of relationships and interaction intensity among users in the YouTube video comment space. The network was constructed as a directed graph where relationships between nodes were determined through reply patterns in the comment section. Nodes represent user accounts, while edges represent directional interactions between users. This means user interactions form clear and separate communication groups, reflecting discourse polarization. This is visualized in Figure 1, where node size represents degree (activity level), showing only a small proportion of nodes possess dominant connections.

Figure 1. Main Network



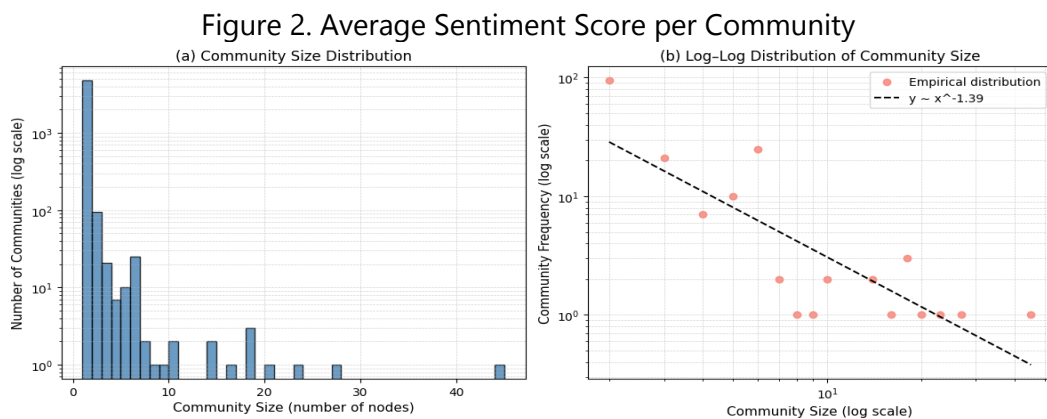
Source: Research data, processed by researchers, 2025

The network analysis shows a sparse and highly fragmented structure, where user interactions form small, separated clusters rather than a unified discussion space. The directed graph built from reply patterns reveals clear divisions between communication groups, with only a few users holding dominant connections. Network metrics reinforce this pattern: a very low average degree (0.108) and density (0.000) indicate minimal connectivity, while the high number of connected components (4,908) demonstrates extreme fragmentation and largely isolated conversations. Despite this, the short diameter (3) and low average path length (1.162) suggest that information still circulates quickly within local clusters. The high modularity value (0.906) confirms strong community separation, and after filtering by Giant Component and Degree  $\geq 2$ , the core network appears composed of several major communities centered around a few key actors who structure interactions within their respective clusters.

## 2. Community Distribution and Structural Inequality

The structural configuration of the YouTube discussion network reveals a striking pattern of extreme fragmentation, which becomes evident when examining the distribution of community sizes generated through Louvain modularity detection. With 5,484 nodes divided into 4,914 distinct communities, the network exhibits a remarkably high modularity score ( $Q = 0.71$ ), indicating strong segmentation and limited intergroup cohesion. Such a high degree of modularity suggests that user interactions

are not embedded in large conversational arenas but instead scattered across thousands of small, self-contained clusters. The prevalence of micro-communities, reflected in an average size of only 1.12 users and a median size of 1, highlights the absence of reciprocal or multi-user exchanges that would typically facilitate discursive consolidation. In essence, the majority of “communities” detected by the algorithm do not represent collective deliberation but rather isolated users whose comments remain structurally and discursively disconnected from the broader conversation.



The extreme imbalance in community sizes reinforces this interpretation. While most communities contain only one or two nodes, the largest cluster comprises merely 45 users, and even the ten largest communities account for only 3.88% of all nodes. This indicates that even the “largest” communities lack the structural mass and interaction density normally associated with influential or cohesive digital publics. The distribution is further characterized by a low Gini coefficient (0.102), which may initially appear counterintuitive, typically, a low Gini would suggest equality. However, in this context, the low Gini does not imply equitable participation across communities; instead, it reflects the overwhelmingly uniform presence of extremely small communities. Paired with the exceedingly high skewness value (21.23), this statistical pattern underscores the degree to which the network is dominated by tiny, atomized clusters and contains almost no mid-sized or large groupings.

These distributional properties are visually confirmed by the two panels in Figure 2. The histogram in panel (a) shows an exponential decay in the frequency of communities as size increases. Hundreds of communities contain only a single

member, while communities larger than five members appear only sporadically, and clusters exceeding ten members become exceptionally rare. This steep decline illustrates how the network lacks intermediate-sized conversational formations that could serve as bridges between individual users and larger public arenas. Meanwhile, the log–log plot in panel (b) approximates a power-law distribution, with a fitted slope of approximately  $-1.39$ . The power-law pattern indicates that the network is scale-free: while a vast number of very small communities dominate the structure, a long tail of slightly larger communities persists, albeit in very small quantities. Such distributions are common in decentralized online spaces where interaction grows spontaneously rather than through formal or coordinated processes.

The presence of a scale-free, micro-community–dominated structure has several implications for how discourse unfolds within this network. First, it suggests that information flow is highly localized, circulating primarily within isolated pockets rather than diffusing across the wider network. This undermines the development of shared narratives or cross-cutting dialogue, as users rarely encounter alternative viewpoints outside their micro-clusters. Second, the absence of large, cohesive communities reduces the likelihood of discursive escalation, coalition formation, or the emergence of dominant frame-setters, actors or groups capable of shaping the broader direction of the conversation. Instead, meaning-making processes occur at the periphery, distributed across numerous clusters with limited reach and minimal interconnectedness.

Third, such fragmentation aligns with contemporary theoretical accounts of digital publics, particularly the notion of *affective micro-publics* (Papacharissi, 2015), wherein users express moral or emotional reactions within small, value-aligned enclaves without engaging in broader deliberative exchange. The structure observed here reflects precisely that dynamic: while users may share outrage, empathy, or moral judgment regarding the case, they do so within micro-communities that lack structural pathways for meaningful intergroup interaction. As a result, the network becomes a mosaic of emotionally resonant but structurally isolated micro-publics, each contributing to the discourse without coalescing into a coherent public sphere.

Fourth, the segmented structure helps explain why emotional polarization remains low despite the morally charged nature of the topic. In many online contexts, particularly political debates, polarization emerges through repeated interaction and reinforcement within densely connected clusters. However, the network here lacks such dense modules; most interactions involve single comments that receive no replies. Without sustained conversational cycles, emotional amplification cannot occur. Fragmentation thus acts as a structural buffer, preventing the formation of antagonistic blocs and keeping sentiment expression largely moderate, as reflected in the high proportion of neutral comments identified in the sentiment analysis.

Finally, this pattern also has methodological implications for interpreting the role of community detection in digital discourse research. In networks where conversational ties are sparse and predominantly non-reciprocal, algorithmically detected communities represent structural segmentation rather than deliberative communities in a sociological sense. The “communities” are algorithmic partitions of limited social meaning, highlighting the need to interpret modularity and clustering results in relation to interaction density. In this dataset, high modularity does not imply the presence of strong sub-publics; rather, it reflects the structural isolation of individual commenters whose contributions remain disconnected from broader discursive flows.

Taken together, these findings suggest that the YouTube comment space surrounding this case does not operate as a unified digital public but rather as an archipelago of tiny, weakly connected islands of discourse. Such a structure constrains the emergence of collective voice, inhibits dialogic exchange, and reinforces the fragmented nature of public opinion on sensitive social issues.

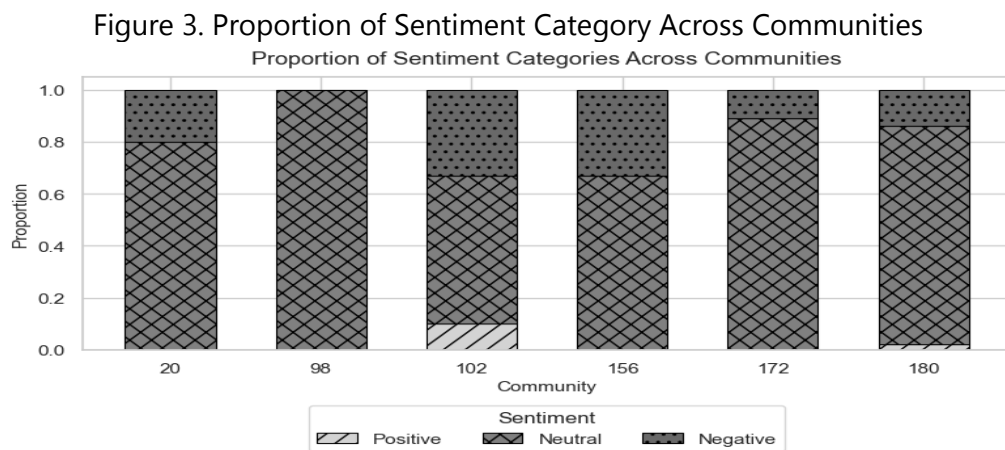
### 3. Community Clusters and Discursive Themes

Community detection reveals a highly fragmented network (modularity = 0.906), where users interact primarily within value-aligned clusters rather than across groups. Six main communities dominate: C180 as a moral-religious justice core; C102 and C20 expressing empathy, spirituality, and fear; C156 and C98 emphasizing social reflection and ethical critique; and C172 driving digital activism. These clusters show discourse shaped more by affective and moral alignment than rational reasoning, aligning with

the concept of affective publics, while limited cross-community connectivity reinforces echo-chamber dynamics that strengthen internal cohesion but restrict broader dialogue.

#### 4. Emotional Polarization Among Communities

Sentiment analysis reveals that the overall emotional expression within the online discourse concerning this case of sexual violence is largely stable and moderate, exhibiting no strong signs of polarization. This is most notably characterized by the pronounced dominance of neutral comments (approximately 77%), then followed by negative (20%) and a small positive portion (3%). This prevalence suggests that users predominantly responded with emotional caution, frequently employing factual statements, prayers, or supportive remarks that refrain from heightened affect.



Source: Research data, processed by researchers, 2025

While neutrality is the overarching pattern, each distinct community exhibits a unique sentiment configuration aligned with its thematic focus:

- Community 156 demonstrates the strongest negative sentiment, which is expressed not as hostility but rather through empathetic, emotionally reflective remarks conveying concern, disappointment, and solidarity with the victim.
- Community 182 is characterized by the most positive and supportive tone.
- Community 102 displays a moderate level of negative sentiment coupled with a minor proportion of positive comments, reflecting a blend of spiritual encouragement and assertive moral appeals.

- d) The largest cluster, Community 180, along with Community 20 (focused on fear and stigma) and Community 172 (associated with digital activism), maintain highly neutral sentiment profiles. In Community 180, this neutrality is primarily framed through moral-religious reasoning, whereas in Communities 20 and 172, it is associated with informational or mobilizing statements.
- e) Community 98, which centers on social ethics and normative critique, emerges as the most emotionally stable, displaying an entirely neutral sentiment distribution.

The exceptionally narrow range of mean sentiment scores (-0.33 to 0.00) across all communities further substantiates the finding that, despite a highly fragmented network structure producing isolated micro-publics, thematic divergence does not translate into significant emotional disparity. Instead of evolving into emotionally opposed blocs, each cluster functions as an internally coherent yet affectively moderate enclave.

This pattern indicates that the YouTube comment space in this context does not serve as a site of intense emotional confrontation, but rather constitutes a constellation of affectively stable, yet isolated, micro-publics

##### 5. Synthesis: Discursive Dynamics and Public Fragmentation

The integrated analysis of network structure and sentiment distribution reveals that this video's comment space operates as a highly fragmented discursive ecosystem. The high modularity value (0.969) and the number of connected components exceeding 4,900 demonstrate a lack of cross-group connectivity, causing each community to develop into a closed discursive space with its own affective logic. In the context of digital communication, this phenomenon can be understood as a form of "public fragmentation", a situation where online interactions do not form a shared deliberative space but rather a collection of micro-communities with internal emotional resonance.

This tendency aligns with Papacharissi's (2015) findings on affective publics, where emotion serves as the primary binder for solidarity in digital spaces. In this case, each community operates based on a specific dominant affect, such as religious morality (C180), social empathy (C156), or digital activism (C172). Although these

differing affective orientations signify a diversity of public expression, the dissociated network structure ultimately restricts interaction between different affective spheres, resulting in emotional fragmentation rather than affective dialogue.

The visualized sentiment distribution results (Figures 5a–b) reinforce this conclusion. Most communities exhibit internal affective consistency, dominated by neutral sentiment (70–90%) with minor variation between positive and negative. This narrow distribution indicates low emotional heterogeneity within each community, reinforcing an echo chamber pattern—a situation where group members reinforce pre-existing, aligned emotions and values.

However, certain communities like C156 and C102 display a more heterogeneous affective pattern, signifying the presence of relatively open empathetic spaces for differing viewpoints. This indicates that not all fragmentation is ideologically closed; some communities retain a reflective dimension and emotional solidarity across diverse experiences.

Overall, these network dynamics illustrate the formation of a layered digital public sphere, where social connection does not necessarily equate to discursive openness. In this context, communities function as affective entities, not merely as discussion groups, but as vessels for emotional expression that reinforce collective identity through morality, empathy, or digital action.

Thus, these results confirm that the analysis of comment networks represents not just the technical relationships between nodes, but also patterns of emotional resonance that form affective micro-publics within contemporary social media spaces.

## **Finding and Discussion**

The findings of this study show that public responses to the sexual violence case presented in the video are shaped by the interaction between moral reasoning, emotional expression, and the symbolic authority of religion. Online discussions involving religious figures are often influenced by moral frameworks embedded in everyday belief systems, resulting in patterns of public judgment that extend beyond the facts of the case, a process aligned with models of moral contagion and identity-

based judgment in digital spaces (Brady et al., 2020; Sung & Lee, 2015). The interaction network reveals a highly fragmented discussion environment, where users tend to engage within small, value-aligned clusters rather than across divergent groups. Such fragmentation aligns with research showing that digital platforms facilitate micro-public formations rather than shared public spheres (Cinelli et al., 2021; Törnberg, 2018).

The largest communities articulate their responses through moral-religious narratives and calls for justice, indicating that religious values serve as a primary interpretive lens in evaluating allegations of wrongdoing. This corresponds with existing scholarship demonstrating that religious authority acts as a powerful heuristic for credibility judgments, shaping how communities respond to accusations involving moral transgression (Metzger & Flanagin, 2013). Meanwhile, the presence of empathy-oriented communities reflects the role of affective alignment in online responses to trauma and violence, reinforcing that digital publics operate through emotional resonance rather than purely rational deliberation (Chakraborty et al., 2020; Norman et al., 2020).

However, the coexistence of comments that question or discredit the victim highlights the persistence of social stigma and victim-blaming attitudes in cases of sexual violence, particularly in patriarchal and religious contexts where honor-based logics often prevail (Ventura et al., 2021).

This suggests that neutrality in this setting does not indicate a lack of involvement but reflects the tension between empathy and deference to religious authority. The predominance of neutral sentiment supports earlier findings that online moral discourse is often characterized by complex affective patterns rather than pure polarization, especially when sacred or institutional values are involved (Brady et al., 2020).

Taken together, these findings indicate that digital discourse on sexual violence involving religious figures does not result in a unified collective stance. Instead, it produces multiple, coexisting moral interpretations that remain structurally separated due to platform-mediated interaction patterns. The comment section operates less as

a deliberative public sphere and more as a constellation of affective and moral micro-publics, shaped by religion, social identity, and emotional alignment, a phenomenon consistent with findings on homophily and echo chambers in online social networks (Himmelboim et al., 2017).

## **CLOSING**

This research shows that public discourse on YouTube about sexual violence involving religious authority is marked by strong structural and emotional fragmentation. Using Mixed Methods Social Network Analysis (MMSNA), the study finds a sparse, highly modular network made up of many small, isolated groups, "affective micro-publics" where users interact mainly within morally and emotionally aligned clusters, limiting cross-community dialogue.

While neutral sentiment dominates, reflecting cautious moral concern rather than sharp polarization, thematic analysis reveals diverse community roles, from religious calls for justice to empathetic support and social critique. This indicates that YouTube serves as a space for negotiating social meaning, but one segmented by moral and emotional boundaries. The study concludes that on sensitive topics mixing religion and morality, YouTube's platform architecture fosters fragmented echo chambers, reinforcing solidarity within groups rather than encouraging broad deliberation, offering insights into digital public opinion formation in Indonesia's cultural context.

## **LIMITATIONS AND RESEARCH OPPORTUNITY**

This study, focused on one YouTube video, has limited generalizability and relies on textual sentiment analysis that may miss subtle emotional cues. The fragmented network restricts tracking opinion changes over time. Future research should explore multiple platforms, cultural contexts, and use longitudinal and multimodal analyses to better understand how moral judgment and credibility form online.

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