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Analysis of The #Sline Social Network on Tiktok

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ABSTRACT: This study analyzes the communication network of the SLine hashtag on TikTok, a digital phenomenon that emerged after the broadcast of the Korean drama S Line in July 2025. This study aims to reveal communication patterns, key actors, and shifts in the meaning of the SLine hashtag from a promotional tag for a fictional drama to a controversial Sline trend among users, especially among the younger generation. This study uses a descriptive quantitative method with Social Network Analysis (SNA) through NodeXL to map network structure, centrality metrics, and cluster formation. The results show a directed network consisting of 942 accounts, dominated by giant components, with 23 sub-communities representing fragmented but connected discourse clusters.

KEYWORDS: SNA, Sline, Korean dramas, trends, TikTok

I. INTRODUCTION

Amidst this wave of digitalization, social media platforms have become a dominant force in shaping complex communication networks. For example, applications such as TikTok have surpassed their basic function as a communication tool, becoming a means of shaping opinions, spreading trends, and even forming new paradigms and cultures. Data from Zebracat shows that the majority of TikTok users globally are Generation Z, reaching 57% (Baumgartner, 2025), making them, as the younger generation, more open to sharing and discussing issues that are considered sensitive and taboo (Nabilah et al., 2024).

In mid-2025, the digital community was abuzz with a new phenomenon that emerged after the airing of a Korean drama titled "S Line." This drama presents a fictional concept of a mysterious red line that appears above everyone's head. In this context, the "red line" symbolizes each individual's intimate experiences. The "red line" phenomenon became a topic of intense discussion on social media, particularly in relation to privacy and social norms. Below is an image of the poster for the phenomenal Korean drama "Sline," quoted from the Tirto.id website (Wahyuningtyas, 2025)

Interestingly, the hashtag #Sline has now spread rapidly on TikTok. Previously, this hashtag was used for promotional purposes to discuss details such as the plot and characters of the drama. However, its meaning has now shifted to content that discusses free sex, sexual experiences, and has even become a trend of humor and viral content on TikTok. This adaptation has undoubtedly created a wave of controversial content, sparking lengthy debates about the boundaries of privacy, the ethics of sharing sexual content in public spaces, and the potential normalization of behaviors that were previously considered sensitive and private.

The spread of content related to sexuality has caused great concern among various groups in society. Moreover, this trend has the potential to encourage promiscuity or promiscuous behavior. Therefore, to understand the #SLine trend more deeply, it is important to use big data-based research. A deep understanding of how trends are formed, who the key actors are, and how information is disseminated can be used as an effort to identify patterns, effective interventions, and can become digital literacy that can be used by the community (Priambodo & Arianto, 2022).

II. METHOD

This study uses social network analysis with descriptive research and a quantitative approach. Descriptive research is used to describe and explain social phenomena, in this case, to observe communication network patterns in the #SLine trend on TikTok. Meanwhile, the quantitative approach and social network analysis are used because the data analyzed comes from digital big data and to identify patterns, structures, and trends in a systematic and measurable manner.

The population studied in this research includes all posts and content referring to the hashtag #SLine on TikTok. This population includes mentions, comments, captions, video descriptions, and other forms of interaction relevant to the topic under study (Eriyanto, 2014). Samples were taken automatically using ASIGTA, which covers all accounts interacting with the hashtag #SLine. The collected sample describes the digital activities of TikTok users related to #SLine during the period of July 10 -26, 2025.

III. LITERACTURE REVIEW

A. Social Network Theory

Social Network Theory, according to (Wasserman & Faust, 1994) is an approach used to analyze the relationships between individuals, groups, or organizations within a larger system. This theory emphasizes the importance of position and relationship structure in influencing social behavior and interaction. Social networks can be analyzed through graphical and mathematical approaches that describe the relationships between actors in a system (Wenlin Liu et al., 2017). Lusher, Robins, & Kremer (Lusher, D et al., 2013) in their book Twitterponential Random Graph Models for Social Networks explain that social network analysis has methods for analyzing the structure of relationships within a set of social entities, providing insights into power, influence, and communication. Social networks are not only important for understanding relationships between individuals but also for seeing how individuals are connected in broader social networks and how this shapes interactions within communities. Social networks are also dynamic and constantly changing, so individuals have the opportunity to gain influence or access to resources that can change. In social networks, relationships between actors are divided into several types:

a. Closed Networks: Where actors are more likely to connect with actors in the same group.
b. Open Networks: Where actors have relationships with a wider range of groups, allowing for a faster flow of information and resources.

(Wasserman & Faust, 1994) state that social networks can be analyzed through graph theory, which has basic elements such as:

a. Nodes: Representing actors or individuals in the network.
b. Edges: Representing the relationship or interaction between two actors.
c. Networks can be described using graphs containing nodes and edges connecting them to form a map. In measuring network structure, there are several concepts involved:

a. Degree: The number of relationships an actor has.
b. Centrality: A measure of the importance of an actor in a network. Several known centrality methods are degree centrality, closeness centrality, and betweenness centrality.
c. Clustering: Describes groups that are interconnected in a network. This provides an indication of how actors in a network form subgroups.

(Wasserman & Faust, 1994) also explain how information, knowledge, influence, and behavior can spread through social networks. Several key processes in this theory are:

a. Diffusion: The spread of information or behavior from one actor to another. Networks that are broader and have more connections will accelerate the spread of information.
b. Homophily: The tendency of individuals to associate with people who are similar to them, whether in terms of social characteristics, values, or outlook on life.
c. Influence: The influence that one actor has over another actor in the network. This can occur due to social proximity or positional power in the network (for example, highly connected actors have more influence).

Proposed a theory that relationships in social networks can vary in strength or depth. These relationships can be distinguished as:

a. Strong Ties: Relationships between individuals who interact frequently and have emotional closeness. These usually occur between family members or close friends.
b. Weak Ties: Relationships that rarely interact, but can have more value because they bridge various groups or individuals that are not directly connected.

Granovetter argues that weak ties are often more valuable in disseminating information, as they connect individuals to differ ent groups or networks. These relationships help expand the reach of information or opportunities, often beyond what strong ties can achieve.Centrality refers to an actor's position in a network that can influence their role in that network. It is divided into sever al categories, namely (Ramadhan, 2020):

a. Degree Centrality: The direct number of relationships an actor has.
b. Closeness Centrality: The extent to which an actor can quickly reach other actors in the network.
c. Betweenness Centrality: The extent to which an actor is between two other unconnected actors, making that actor a connector in the network. Actors with high centrality usually have greater access to information or resources in the network. Social network theory also includes techniques for measuring network structure and relationships in social networks, which include:
d. Eigenvector Centrality: Measuring how influential actors are becomes a reference for other important actors.

B. Big Data in Social Network Analysis

Big Data plays an important role as the main source for analyzing communication patterns, public opinion, and social dynamics in real time and on a large scale. Big data has five main characteristics (Mukhlis & Pipin, 2024):

a. Volume, Big data has a very large amount of data
b. Velocity, The speed of data flow obtained
c. Variety, Big data covers various types of data (such as images, text, video, metadata, and others). In social media, big data includes billions of digital interactions such as posts, comments, retweets, shares, likes, and user profile data.
d. Veracity, related to the reliability, quality, and accuracy of data.
e. Value, explains the economic or strategic value that can be obtained from data analysis

According to Dr. Irwan Dwi Arianto (2021), in big data-based social research from social media, there are two main approaches to sampling (Suratnoaji, C., & Arianto, I. D., 2021):

a. Convenience sampling
A strategy that utilizes the most accessible data, making it more efficient in terms of time and cost. However, it has the disadvantage of significant potential bias.
b. Random sampling
A strategy that aims to give every element in the population an equal chance of being selected as a sample. This results in a more representative sample and allows for stronger generalization. However, the disadvantage is that the data is still massive, making it more complex and expensive.

The use of big data on social media is often combined with the Social Network Analysis (SNA) method, which serves to map the structure and patterns of relationships between actors in a network (Suratnoaji, C., Nurhadi, & Candrasari, Y., 2019). In this context, data such as mentions, retweets, likes, and replies act as connectors between users, which can then be depicted in the form of a graph. Thus, this analysis can identify key actors, discursive clusters, and the centrality of information that dominate s the spread of an issue/trend in the digital space (Priambodo & Arianto, 2022).

IV. RESULTS AND DISCUSSION

A. #SLine Hashtag Communication Network Pattern

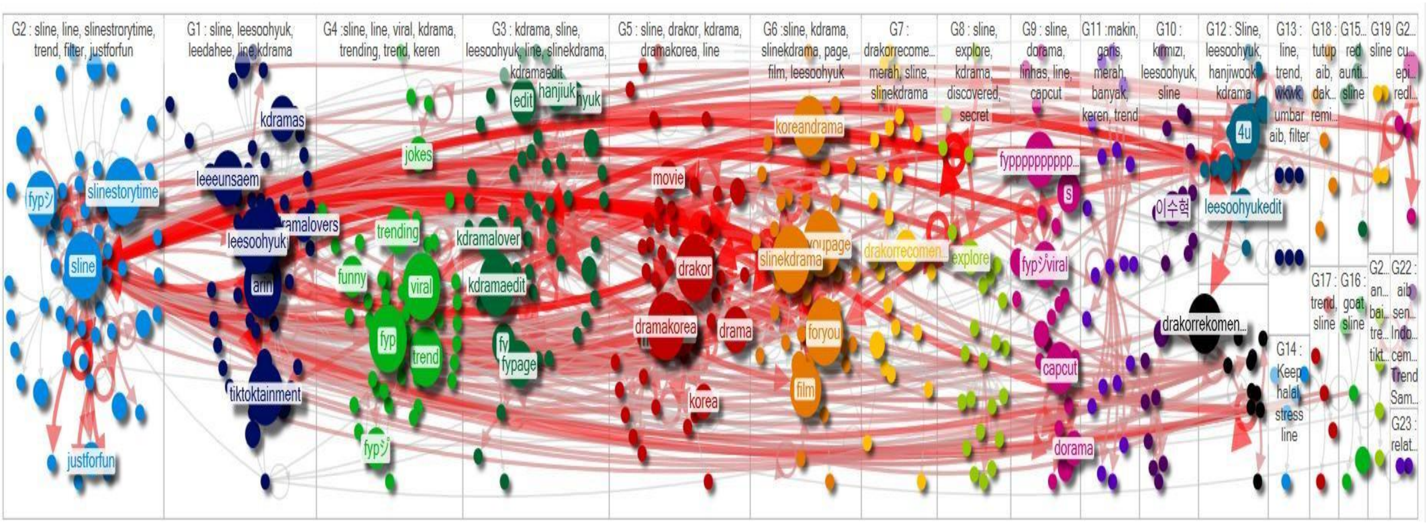
In this study, communication network analysis of the #Sline trend on the TikTok platform was conducted using NodeXL Basic software version 1.0.1.540, with a Social Network Analysis (SNA) approach. The communication network of the #Sline hashtag on TikTok shows a directed network structure. In the context of SNA, a directed network has a specific direction of information flow from one actor to another, thereby revealing a picture of passive and active actors in the communication tha t is formed (Eriyanto, 2014). From the analysis of the entire #Sline network on TikTok, which was formed from July 10 to 26, 2025, a network structure was formed that was dominated by a very large main component consisting of 942 accounts/actors involved and forming 1,844 connections between users. Interestingly, there are only 654 unique relationships with low density (0.0039) and fairly high modularity (0.30608). This indicates that interactions between accounts are not very dense and there is minimal cross-group collaboration. Actors tended to engage in repeated interactions or create Sline content repeatedly, thereby creating sustainable engagement. This phenomenon indicates that the #Sline discourse is not a momentary viral content, but has the potential to become sustained engagement, where content related to the Sline trend is produced and communicated consistently and continuously, leading to ongoing interactions among users, thereby creating discursive persistence that reinforces the sustainability of the trend (Imran, 2013).

Meanwhile, there are nine isolated actors (single-vertex components) that are not connected at all to the main SLine trend network. In SNA terminology, isolate nodes or isolates are actors that are disconnected from the network and have no connection to the main components (Eriyanto, 2014). The existence of isolated actors can be caused by various factors, such as inappropriate posting timing so that content about SLine does not get optimal visibility, platform algorithms that do not prioritize their Sline content or do not make it to the FYP, Sline content that is too niche to get engagement, or late adopters who joined when the Sline trend was already starting to fade. These isolated actors can be called minority voices whose existence is recorded in the network but do not have sufficient discursive power to influence the majority narrative (Wenlin Liu et al., 2017).

The high number of self loops (306 out of a total of 1,844 edges, or around 16.5%) indicates the consistency of Sline-themed content production by content creators. This strategy leverages TikTok's algorithm, which prioritizes consistency in posting and sustained engagement. By producing serial content with the same theme, the chances of appearing on the For You Page (FYP) are higher for users who have previously interacted with #Sline content (Gerbaudo, 2024). In the context of the controversial #Sline trend, consistent content production through self-loops can be a mechanism for normalization. The logic behind this is that the more often #Sline-themed content appears in users' feeds, the more accustomed they become to the discourse, thereby blurring their sensitivity to issues that are actually sensitive and controversial (Montoya et al., 2017).

The characteristics of a small-world network are clearly seen from the network diameter of 8 with an average geodesic distance of 3.41. A network diameter of 8 indicates that information only needs to pass through 8 intermediaries to spread from one end to the other, while an average geodesic distance of 3.41 shows that, in general, information only needs 3-4 intermediaries to spread from one actor to any other actor in the network (Watts & Strogatz, 1998). This small-world network characteristic can explain why the #Sline trend went viral so quickly on TikTok even though the network is sparse with a graph density of only 0.37%. This is because the existence of hub nodes (actors with many connections) facilitates the rapid diffusion of information to various parts of the network. The modularity value of 0.306831 in the #Sline network indicates a fairly low value, meaning that even though there are 23 clusters, they are not truly separate, but rather each cluster is still interconnected and overlapping, forming one large cohesive cluster with subgroups within it that continue to interact with each other. This fragmentation exp lains that even though all clusters discuss #Sline, each cluster has different interpretations and content focuses between clusters, making the Sline discourse on TikTok increasingly complex. In the #Sline network on TikTok, a reciprocity value of 0 means that there are no reciprocal interactions in the entire network.

This study uses the Harel Koren Fast Multiscale model to describe existing graphs because this model has the ability to handle large graphs efficiently and can also see community structures and hierarchical clustering patterns where clusters with high internal connections are automatically positioned cohesively and spatially separated from other clusters, so that the discursive persistence and sustained engagement that exist in social networks can be understood (Harel, D. & Koren, 2002). The following is the result of the Harel Koren Fast Multiscale graph visualization in the Sline network analysis on TikTok:



Gambar 4. 1 Visual Graphics #Sline on TikTok

From the visualization generated by the Harel Koren Fast Multiscale algorithm in the Sline network analysis on TikTok, it can be seen that the graph forms 23 different clusters (G1 to G23) that can be distinguished by the different colors in each cluster. Each cluster is positioned spatially based on the closeness of the cluster relationships. Clusters with high internal connections (high intra-cluster density) will be positioned closer together and more cohesively, while clusters with minimal connections to other clusters (low inter-cluster density) will automatically be positioned further away at the edges of the graph.

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This layout produces an informative picture with a clear hierarchical structure that reflects the differentiation of discursive power between communities. Visually, there are three categories of clusters based on size and position (Rheswary et al., 2024):

1. Central large clusters, there are several large clusters such as (G1.G2,G3,G4,G5) positioned in the center of the visualization with relatively large node sizes and very dense internal connections, where the majority of #Sline discourse occurs in these clusters. Thus, these clusters function as the core of the network, with extensive connections not only internally (within the cluster) but also externally (to other clusters).
2. Peripheral middle clusters, there are middle clusters (G6, G8, G9) positioned around the large central clusters. These clusters are smaller in size and have more specific connections, functioning as bridges or satellites that connect the majority of #Sline discourse with more specific niche communities.
3. Small marginal clusters, there are small clusters such as (G13, G15, G18, G21, G22), these clusters represent niche communities with very specific content or outside the center of the topic of discussion. Their marginal position means that they have minimal connections with mainstream discourse, often developing relatively isolated echo chambers.

The connection pattern seen from the visualization of the #Sline communication network on TikTok shows a highly connected network structure in the center with very dense red lines forming a spider web-like pattern. This indicates a high level of interaction between actors in the main component (giant component), which covers 98% of the entire network. Likewise, the density of connections in the center illustrates how #Sline content spreads very quickly. The information does not spread linearly, but rather spreads in many directions at once with many overlapping paths. This makes the trend stronger and longer lasting because if one path is cut off, there are still other paths that can continue to spread the information. Meanwhile, on the edges of the visualization, there are small clusters with few connecting lines to the large cluster in the center, indicating that there are certain sub-communities that have their own conversations and interaction patterns, separate from the main discussion. These small clusters can be likened to private chat groups discussing the same topic about #Sline, but with different approaches and perspectives from those discussed in the large cluster. As a result, they are not likely to be influenced by or influence the majority discourse (Eidi et al., 2020).

From the existing cluster patterns, we can understand how the SLine trend was formed on TikTok. The process of forming the sline trend on TikTok began with the creation of several main groups (clusters), each with a specific theme and function within the discussion ecosystem. Initially, the promotion and introduction clusters (clusters G1 & G2) began to introduce the term “sline” in the context of Korean dramas—through introductory content, initial stories, and narrative encouragement about the unique aspect of Korean dramas. SLine, which visualizes a red line above each person's head, is interpreted as a sex line (the number of sexual relationships each person has had/body count). At this stage, hashtags such as #sline, #slinestorytime, and #kdrama began to appear frequently and formed an early community that connected old and new users.

As the discussion developed, the promotion and entertainment clusters (G3 & G4) became increasingly active in promoting creative content and provoking engagement with comedy, memes, and challenges. In this process, universal hashtags such as #fyp, #viral, and #funny became the main supporters that expanded the reach of the sline trend to a wider audience, spreading the sline narrative outside the Korean drama community. The connection between clusters also grew stronger through co-occurrence and content sharing between groups, driven by actors and hashtags with high degree and betweenness centrality. Furthermore, the fandom and niche community clusters (G5-G7) began to play a role in amplifying the trend. Influencers, Korean drama fans (#leesohyuk, #drakor, #dramakoreaedit), and recommendation accounts produced follow-up content such as reviews, recommendations, remixes, and interpretations of the sline trend according to the interests of the audience group. This process formed a double path to virality: through the main path of popular hashtags and the alternative path of minor clusters, with thick edges connecting central nodes.

Other thematic clusters such as video editing (#capcut), exploration (#explore), and humor/netizen interactions (G8-G13) also participate in this process. These clusters serve to enrich content variety and increase interconnectivity between topics. It is this diverse cluster dynamics that transforms sline from a local or niche trend limited to the Korean drama community into a viral phenomenon.This narrative describes the organic stages of trend virality on TikTok—not just the work of a single account, but the result of distribution and interaction among power centers, clusters, and digital actors. This process is supported by the symbolic power of popular hashtags, platform algorithms that recommend and distribute content to various clusters, and the contagiousn ess of an initial community as a platform for introduction, creative amplification by the fandom, then distribution across clusters and actors, to the stabilization and diversification of content by many increasingly interconnected thematic groups that support the massive spread of the trend on TikTok.

B. Actor Centrality Analysis: Identification of Key User Accounts

Actor centrality is a useful measure for identifying key actors in a network, so it is not enough to look only at individual attributes; one must also look at how rational structures form discursive power and significant influence in the network. In this study, actor centrality analysis of the #Sline hashtag communication network on TikTok uses four main centrality measurements, namely Degree Centrality, Betweeness Centrality, Closeness Centrality, and Eigenvector Centrality(Derr, 2021). The following is a table of actor centrality in the network:

Vertex	In-Degr	Out-Degre	de ee	Betweenn Centrality	Closeness Centrality	Eigenvect Centrality	Rank	Clustering Coefficien	Reciprocated Vertex Pair Ra	vertex type	author	author_f	author_follow
youncxx	1	40	41	20387,265	0,001	0,010	9,484	0,000	0,000	User_Account	youncxx	nasa	1128
drakorapril	1	32	33	18148,347	0,001	0,008	8,136	0,000	0,000	User_Account	drakorapril	Drakorapril	1581
pacarwooseok_oppa	1	28	29	14252,875	0,001	0,010	6,160	0,000	0,000	User_Account	pacarwooseok_oppa	thirakookie |	86300
batulicin_terkini01	1	20	21	342,000	0,053	0,000	9,488	0,000	0,000	User_Account	batulicin_terkini01	BATULICIN	89500
clubkdrama	1	18	19	7031,537	0,001	0,007	3,969	0,000	0,000	User_Account	clubkdrama	KDRAMAS	144300
yovincaprafika	1	16	17	4563,946	0,001	0,009	3,183	0,000	0,000	User_Account	yovincaprafika	Yovinca Pra	199600
krmllize	1	15	16	6347,640	0,001	0,007	3,505	0,000	0,000	User_Account	krmllize	krmllize	3766
surabiyt0t	1	14	15	5499,293	0,001	0,007	3,018	0,000	0,000	User_Account	surabiyt0t	netflix start f	381
febbrypp_	1	14	15	5000,391	0,001	0,006	2,873	0,000	0,000	User_Account	febbrypp_	febry	1575
akmaansir	1	13	14	6009,211	0,001	0,007	3,182	0,000	0,000	User_Account	akmaansir	rainbowjelly	1600
irfan_fanoo	1	13	14	2753,502	0,001	0,008	2,481	0,000	0,000	User_Account	irfan_fanoo	IRFAN FAN	523600
bekesah.co	1	11	12	5658,020	0,001	0,005	3,024	0,000	0,000	User_Account	bekesah.co	BEKESAH	5955
rosini99	1	11	12	4933,613	0,001	0,005	2,727	0,000	0,000	User_Account			
nwlaskf.kaf	1	11	12	4817,537	0,001	0,004	2,808	0,000	0,000	User_Account	nwlaskf.kaf	call me suh	1535
mama_bunju	1	11	12	1990,123	0,001	0,007	2,064	0,000	0,000	User_Account	mama_bunju	Mama Bunj	643

Gambar 4. 2 Label Actor Centrality in the Network

On the #Sline trend network on TikTok, the Youncxx account ranks highest in degree centrality with a total of 41 interactions (from 40 out degrees and 1 in degree). This shows that this account is an actor who plays a role as a very activ e and consistent content broadcaster in producing content and interacting with various actors and hashtags in the #SLine network. This pattern is characteristic of early adopters on TikTok for trending topics. The advantage of this pattern is that it has distinctive features that can serve as a model for other users and benefit from the algorithm, as consistent posts are prioritized by Tik Tok's algorithm (Spells, 2024). In the context of social media influencers, the Youncxx account on TikTok falls into the nano influencer category because it only has 1,128 followers (Anjany, 2025). However, despite having a small number of followers, this account has the highest betweenness centrality in the network at 21,234 and the highest eigenvector centrality alongside the pacarwooseok_opa account at 0.010. This means that the connections of the youncxx account are in a strategic position that connects with various different clusters and is linked to other important actors in the network.

In second place is the Drakorapril account with a degree value of 33 (out degree 32 and in degree 1). This account has a profile very similar to the Yoncxx account, which acts as a very active and consistent content broadcaster in producing content and interacting with various actors and hashtags in the #SLine network. Betwenness centrality of 18.913 ranks second after youncxx, indicating that drakorapril is not only active in terms of quantity but also plays an important role as an inter -cluster broadcaster connecting the K-Drama fandom with a wider range of Tiktok users. This account has 1,581 followers and, as the name suggests, the content on the dramakoreaapril account focuses on K-Drama reviews, fandom content, and drama recommendations. The high eigenvector value of 0.008 explains that drakorapril is connected to high-quality actors in the network, possibly fellow K-Drama content creators who are also active in the #Sline trend.

Next, ranking third in degree centrality is Pacarwooseok_oppa with a degree of 29 (out degree 29 and in degree 1). In the entertainment content niche on TikTok, this account is categorized as a micro influencer because it has 86,300 followers (Anjany, 2025). Micro influencers are typically known for having a specific niche. Pacarwooseok_oppa is an entertainment content creator who focuses on recommending dramas and movies. The use of the username "pacarwooseok_oppa" is an attractive personal branding strategy because it is synonymous with being an authentic K-Drama fan, making it more credible and relatable to the target audience. This can be seen from the betweenness centrality ranking in third place at 14,820 and the eigenvector centrality ranking in the highest position at 0.010, meaning that this account plays an important role in connecting with var ious communities and has quality connections to important accounts on TikTok. Such high-quality connections can be an amplification advantage, where the content is likely to be shared by other higher-level accounts, thereby expanding its user reach.

From the SLine trend network on TikTok, it can be seen that the account with the highest closeness centrality is mahdi_abang (1.0), followed by piixd_ (0.5) and silversmoke (0.5). This means that these three accounts play the role of "fas test broadcasters," enabling them to reach other accounts quickly. Thus, all Sline information, trends, or content can spread to many other accounts in a short time. Interestingly, upon closer observation, these three accounts are not the main brokers in the network. The main brokers are the accounts youncxx, drakorapril, and pacarwooseok_ap, which actually have a very low closeness value of 0.001. This can be interpreted to mean that in the SLine trend network, it is not always the main brokers that act as the fastest broadcasters. Thus, it can be interpreted that in the Sline TikTok trend network, the centrality of actors in the network is distributed according to their type and function: there are accounts that are optimal for viralizing a trend widely, and ther e are those that function as gatekeepers of information between various clusters. The combination of broadcasters and strategic brokers supports more efficient virality while maintaining the network structure so that it does not become too centralized. These findings show that the virality of SLine trends is not only dependent on one central account, but is the result of the collective contribution of various types of key actors with different roles in the network.

C. Pseudopower in SLine Networks on TikTok

Pseudo power is a finding in the SLine trend network on TikTok, considering that various discourses in each cluster can reveal why structures that appear solid become pseudo power on the TikTok platform (Arianto et al., 2023). There are 942 accounts involved, but only 654 unique relationships with low density (0.0039) and fairly high modularity (0.30608). This sho ws that interactions between accounts are not very dense and there is minimal cross-group collaboration. Several top accounts such as youncxx and drakorapril occupy the top positions based on high degree and betweenness values, but their closeness and eigenvector values are low. These findings show that although these accounts appear to have the power to act as intermediaries in the communication network, their effectiveness in building interactions is still low. This is reinforced by data from 13 sepa rate network components, the majority of which consist of only one member.

The cluster data and top hashtags also reinforce the pseudo power pattern. For example, hashtags such as #sline #kdrama #drakor generally appear in trending viral themes, drama promotions, and reviews. These hashtags tend to be symbols of temporary popularity, as seen in clusters G1 to G6, where each cluster forms its own separate sphere of activity without stro ng interaction with other groups. This phenomenon illustrates pseudo power, where the narrative strength and dominance of actors appear significant but are actually weak in forming real collaboration within the network (Arianto, 2023). However, despite the presence of pseudo power, the Sline trend can still go viral with a wide reach. This is due to the support of symbolic power, platform algorithms, and the contagious nature of viral content, which allows the Sline trend to spread across various communities (Gerbaudo, 2024).

CONCLUSION

This study found that the #SLine phenomenon on TikTok has evolved from simply promoting Korean dramas to becoming a discursive and controversial trend, especially among the younger generation. Through network analysis, 942 accounts were identified as belonging to 23 sub-communities, forming one major component of a very large network with a small-world network structure, where information spreads easily and quickly between users. The communication pattern in the network is dominated by central connectivity (giant component), but with minimal cross-group collaboration, indicating discourse fragmentation across various sub-communities. Accounts such as youncxx, drakorapril, and pacarwooseokoppa were central actors as broadcasters and digital brokers, although the effectiveness of cross-cluster interactions was relatively low (pseudo- power). Repetitive content and consistency in posts (self-loops) supported the normalization and virality of trends in the TikTok algorithm.

This study reveals that the spread of the #SLine hashtag is not driven by a single major actor, but rather by the collective contribution of various types of users who act as rapid disseminators and gatekeepers of information between clusters. Virality can occur organically through interaction, content distribution, and the symbolic power of hashtags and the TikTok algorithm, the reby strengthening discourse and massively expanding the reach of trends. The phenomenon of pseudo-power was also identified in the network, where the narrative dominance and popularity of several accounts did not actually result in real collaboration between communities, but were still able to drive virality because they were supported by the nature of the platform and algorithm as well as the contagious nature of viral content. The results of this analysis indicate the need for digital literacy to understand, anticipate, and respond to the threats of the SLine trend in the context of ethics, privacy, and the potential normalization of sensitive behavior on social media.

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