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Engagement Patterns of Educational Content on TikTok

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ABSTRACT

The rapid development of digital technology has contributed to the increasing use of social media, particularly TikTok, which functions not only as an entertainment platform but also as a medium for distributing educational content through hashtags such as *#edukasi*. However, not all educational content generates the same level of engagement, making further analysis necessary to understand the interaction patterns formed within the platform. This study aims to analyze engagement patterns of educational content on TikTok and identify the dominant hashtags appearing alongside *#edukasi* within each cluster. The methods employed in this study include K-Means Clustering to group content based on engagement characteristics and Social Network Analysis (SNA) to examine relationships among hashtags. The findings indicate the formation of two clusters with different engagement characteristics, namely high-engagement and low-engagement clusters. Network analysis reveals that the low-engagement cluster forms several communities associated with topics such as facts, health, and children's education, while the high-engagement cluster is dominated by hashtags related to educational toys, such as *#mainananak* and *#mainanedukasi*. These results demonstrate that the combination of clustering methods and social network analysis is effective in identifying engagement patterns and hashtag relationships in educational TikTok content.

Keyword: Engagement, Hashtag, Educational Content, TikTok, K-Means, Social Network Analysis

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1. INTRODUCTION

The rapid development of digital technology has encouraged the increasing use of social media as a platform for interaction, entertainment, and information sharing. One of the platforms experiencing significant growth is TikTok. According to the We Are Social and Meltwater report in 2025, Indonesia ranks second globally after the United States, with approximately 108 million users aged 18 and older [1]. These figures indicate that TikTok has extensive reach and strong engagement potential.

TikTok functions not only as an entertainment platform but is also utilized as a tool for communication, digital marketing, and the dissemination of educational content. The use of hashtags has become an important element in content distribution because it facilitates content

categorization and information discovery. One example of hashtag usage is #education, which indicates a trend of using TikTok as a learning platform.

However, not all educational content achieves the same level of engagement. Some content achieves high engagement, while others have relatively low engagement. Research shows that factors such as hashtag usage, upload time, and video duration influence engagement levels [2]. Additionally, user interaction also contributes to increased engagement [3]. This indicates that further analysis is needed to understand the patterns of interaction that emerge.

The large volume of data generated from the use of the hashtag #edukasi presents challenges in data analysis. Therefore, a method capable of grouping and simplifying the data is required. K-Means Clustering is used to group content based on similarities in engagement characteristics [4], while Social Network Analysis (SNA) is used to analyze the connections between hashtags and identify communities within the network [5].

Based on these considerations, this study proposes a combination of K-Means Clustering and SNA to analyze educational content on TikTok. This approach is expected to provide a more comprehensive understanding of engagement patterns and the structure of relationships between hashtags, thereby contributing to the development of more effective educational content strategies.

2. METHODS

This study is a quantitative research project that employs a data analysis approach based on the Knowledge Discovery in Databases (KDD) framework, which includes the steps of data selection, preprocessing, transformation, data mining, interpretation, and evaluation. The KDD framework was chosen because it is capable of systematically processing large amounts of data to identify meaningful patterns from the dataset [6]. The research workflow used in this study is shown in Figure 1.

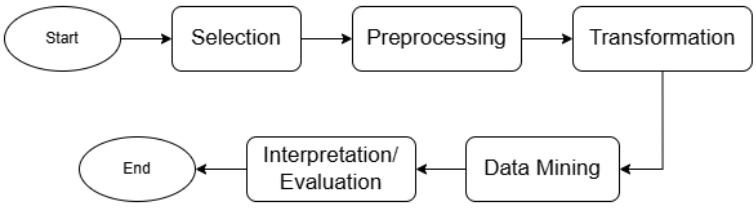


Figure 1. Knowledge Data Discovery

The data used in this study were secondary data in the form of TikTok content tagged with *#edukasi*, collected through a scraping technique. During the preprocessing step, data cleaning was performed to remove irrelevant data. Furthermore, in the transformation step, data standardization was applied to ensure comparable scales among variables for optimal analysis. The data mining process utilized the K-Means Clustering algorithm to group content based on engagement characteristics, such as the number of likes, comments, shares, and views using Euclidean distance measurement [7]. The number of clusters was determined based on evaluation results to obtain the optimal clustering outcomes. Additionally, Social Network Analysis (SNA) is used to analyze the connections between hashtags and identify communities formed within the network. The clustering results were subsequently evaluated to ensure the quality of the generated clusters, thereby providing an overview of engagement patterns and hashtag relationships in educational content on TikTok.

3. RESULTS AND DISCUSSION

This section focuses on presenting and discussing the results of data analysis at each step of the research, including data selection, preprocessing, and data transformation to the clustering process and the interpretation of network analysis results. The discussion is conducted systematically to demonstrate how engagement patterns in educational TikTok content are formed and how relationships among hashtags were identified from the analysis results.

3.1 Data Selection

The data selection was conducted to identify data relevant to the research objective, spesifically analyzing engagement patterns in educational content on TikTok. The data were obtained through a web scraping process, an automated technique for collecting data from web pages [8]. The scraping process was performed using the Apify platform with the keyword "*#edukasi*." All scraped data was then saved in Excel format to facilitate further processing and analysis.

The data collection process generated 12,000 TikTok content records containing several attributes related to engagement and network analysis requirements. The variables used in this study are shown in Table 1.

Table 1. Dataset Variables

Variable	Description
Likes	Number of likes on the video
Comments	Number of comments on the video
Shares	Number of shares on the video
Plays	Number of video views
Duration	Duration of the video
Music Original	Information on the use of original music in the video
Text	Caption text and hashtags used in the content

The attributes likes, comments, shares, views, saves, duration, and original music are used in the clustering process because they represent engagement characteristics in TikTok content [7]. Meanwhile, the caption attribute is used in the Social Network Analysis (SNA) process to identify connections between hashtags that appear in the content [5].

3.2 Preprocessing

The preprocessing step was conducted to ensure that the data were clean and ready for the analysis process [9]. At this step, data cleaning was performed by removing missing values and duplicate records, as well as adjusting the data format for each variable. After the cleaning process, the dataset used in this study consisted of 11.191 data points out of the initial total of 12.000. In addition, numerical variables such as likes, comments, shares, views, saves, and duration were converted into numerical formats to be used in the clustering process.

In the Social Network Analysis (SNA) process, text cleaning was applied to the caption attribute through hashtag filtering. This step involved removing irrelevant hashtags such as #fyp, #viral, and other general hashtags to ensure that the analysis remained focused on the

context of educational content. Duplicate hashtags were also removed to avoid repeated relationships within the network. This process aimed to ensure that the relationships formed among hashtags could represent content topics more clearly [5]. Examples of the hashtag filtering results are shown in Table 2.

Table 2. Example of Hashtag Filtering

Caption	Caption After Filtering
kita dipaksa bisa semua mata pelajaran, sedang gurunya aja ada 12! #sekolah #sistem #peraturan #murid #guru #edukasi #foryoupage	kita dipaksa bisa semua mata pelajaran, sedang gurunya aja ada 12! #sekolah #sistem #peraturan #murid #guru #edukasi
Ketahui tujuan akhir hidup lu #fyp #motivation #tiktok #edukasi	ketahui tujuan akhir hidup lu #motivation #edukasi
Kenali tanda saraf kejepit tangan CTS. #doktersarafku #edukasitiktok #cts #sarafkejepit	kenali tanda saraf kejepit tangan cts. #doktersarafku #cts #sarafkejepit

3.3 Transformation

The transformation is performed to convert the data into a format suitable for analysis process [9]. In the clustering process, the categorical variable music_original was transformed into numerical form through an encoding process, where the value True was converted into 1 and False into 0. The variables selected for the clustering process included likes, comments, shares, views, duration, and music_original. After that, the data is standardized using StandardScaler to ensure that all variables had comparable scales and did not dominate the distance calculation process in the K-Means algorithm [10].

In the Social Network Analysis (SNA) process, hashtag splitting is performed to separate each hashtag found in the text/caption variable. This process involves extracting words preceded by the hash symbol (#), then separating each hashtag into several distinct columns, namely hashtag 1 through hashtag 10. This step was intended to allow each hashtag to be identified individually and to facilitate the formation of relationships between hashtags within the network. Furthermore, the data is transformed into a network structure consisting of source, target, and weight based on the co-occurrence of hashtags within the same content [11]. Each hashtag pair was represented in the source and target columns, while the weight column indicates the frequency of that hashtag pairs occurrences in the dataset. This structure serves as the foundation for constructing the hashtag network during the Social Network Analysis step. Examples of the transformed network data structure are shown in Table 3.

Table 3. Example of Source, Target, and Weight Data Structure

Source	Target	Weight
#education	#edukasi	231
#inspiration	#education	176
#inspiration	#edukasi	176
#mainanedukasi	#mainananak	91
#edukasi	#edukasikesehatan	63

3.4 K-Means Clustering

Before the clustering process was carried out, the data dimensionality was first reduced using Principal Component Analysis (PCA) to reduce data complexity without eliminating important information [12]. PCA was applied to the standardized data so that each variable had a comparable scale. This process involved calculating the explained variance and cumulative variance values for each principal component. The calculation results are presented in Table 4.

Table 4. PCA Results

Component	Explained Variance (%)	Cumulative (%)
PC1	40.93	40.93
PC2	18.32	59.25
PC3	15.73	74.98
PC4	12.27	87.26
PC5	8.91	96.17
PC6	3.82	100.00

Based on the PCA results, five principal components were selected because they retained a cumulative variance of 96.17%. This value indicates that most of the information and patterns within the data could still be well represented after the dimensionality reduction process. The use of five components was also considered more optimal than four components because, at a cumulative variance of 87.26%, some data variation had not yet been fully represented. Excessive dimensionality reduction may result in the loss of important patterns that could affect the clustering process. Therefore, five principal components were selected to ensure that the data structure remained representative before clustering was performed.

Next, the optimal number of clusters was determined using the Silhouette Score method. This method is used to evaluate the quality of clustering based on the degree of data proximity within clusters and the separation between clusters [13]. The test results are shown in Figure 2.

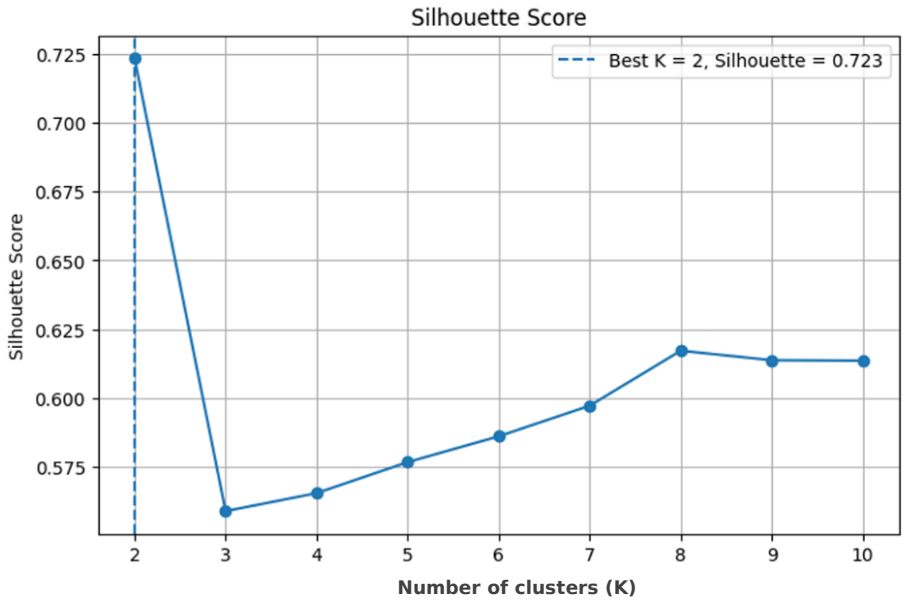


Figure 2. Silhouette Score Graph

Based on the test results, the highest Silhouette Score was obtained at K = 2, with a value of 0.723. This value indicates that dividing the data into two clusters produced the best cluster structure compared to other numbers of clusters. Therefore, this study used K = 2 in the clustering process using K-Means algorithm.

The clustering process was then performed on the data resulting from PCA dimensionality reduction using the K-Means algorithm. The K-Means algorithm works by grouping data based on proximity to the cluster center (centroid) using Euclidean distance calculations [7]. The clustering results are shown in Table 5.

Table 5. Clustering Results Distribution

Cluster	Number of Data
0	8055
1	3136

Based on the clustering results, Cluster 0 contains a significantly larger volume of data than Cluster 1. This distribution difference indicates that engagement patterns in #edukasi TikTok content are not evenly distributed and form two main engagement characteristic groups based on the selected engagement variables.

To ensure the quality of the formed clusters, additional evaluations were conducted using Silhouette Score and Davies-Bouldin Index (DBI). Silhouette Score was used to measure the similarity of data points within their own cluster compared to other clusters, while Davies-Bouldin Index (DBI) is used to measure the degree of similarity within clusters and the differences between clusters [14]. The evaluation results are shown in Table 6.

Table 6. Clustering Evaluation Results

Nilai k-	Silhouette Score	Davies Bouldin Index
2	0.7219	1.0089
3	0.5697	0.9686
4	0.5766	0.9589
5	0.5881	1.0528
6	0.5983	0.7415
7	0.6084	0.8579
8	0.6288	0.8666
9	0.6227	0.9318
10	0.6297	0.9433

Based on the evaluation results, the highest Silhouette Score was obtained at K = 2 with a score of 0.7219. This result indicates that the resulting clusters possessed good compactness and relatively clear separation. As the number of clusters increased, the Silhouette Score tended to decrease, indicating that adding more clusters did not significantly improve clustering quality.

Additional evaluation using Davies-Bouldin Index was also conducted to provide another perspective on clustering quality. Based on the evaluation results, the lowest DBI

value was obtained at K = 6 with a value of 0.7415. Nevertheless, this study still used K = 2 because it produced a clearer and more interpretable clustering structure for describing engagement patterns in educational content on TikTok.

Furthermore, clustering interpretation was conducted using two-dimensional PCA visualization to examine the data distribution within each cluster. The visualization results are shown in Figure 3.

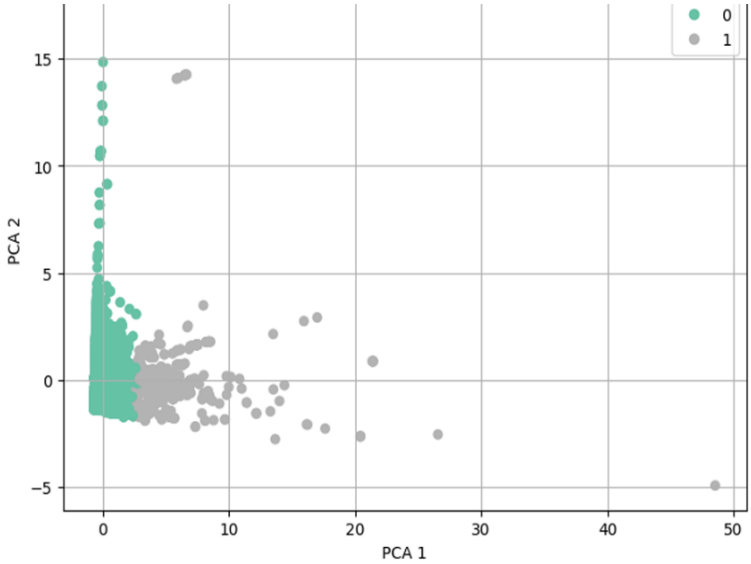


Figure 3. PCA Visualization of Clustering Results

In the visualization, each point represents a TikTok video containing the hashtag *#edukasi*, while the colors indicate the cluster labels generated by K-Means. The visualization shows that the data are divided into two relatively distinct groups. Cluster 0 has a tighter distribution of data, while Cluster 1 has a wider distribution, indicating a greater variety of engagement patterns.

In addition to the PCA visualization, the distribution of data within each cluster was also visualized using a bar chart, as shown in Figure 4.

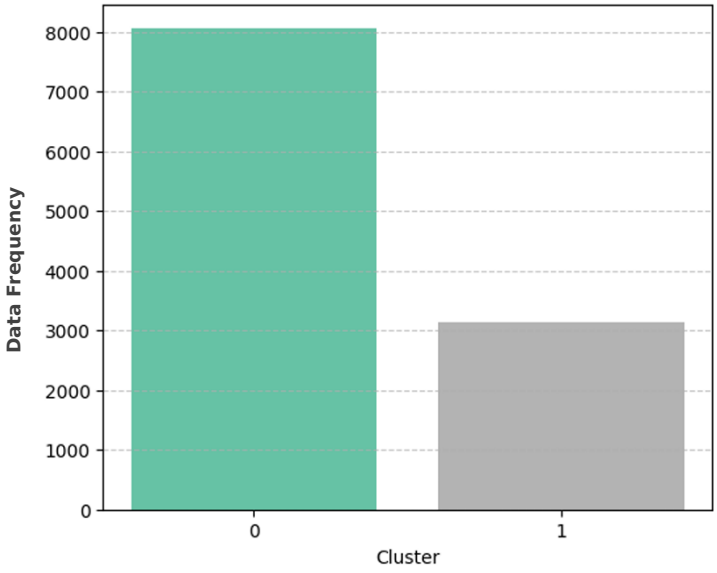


Figure 4. Distribution of Data in Each Cluster

Based on the data distribution, Cluster 0 has the largest number of members compared to Cluster 1. This indicates that most *#edukasi* content on TikTok exhibits relatively similar engagement patterns and tends to belong to the low to moderate engagement category. To better understand the characteristics of each cluster, descriptive statistical analysis was conducted on each engagement variable. The analysis results for Cluster 0 and Cluster 1 are presented in Tables 8 and 9.

Table 7. Descriptive Statistics of Cluster 0

Metrik	Count	Mean	Std	Min	Max
likes	10645.00	61367.01	128563.83	0.00	1200000.00
comment	10645.00	1540.56	3798.00	0.00	43900.00
shares	10645.00	6435.57	16826.68	0.00	252600.00
plays	10645.00	1854120.94	3365909.05	0.00	31800000.00
duration	10645.00	61.94	103.22	0.00	2668.00
music_original	10645.00	0.72	0.45	0.00	1.00

Table 8. Descriptive Statistics of Cluster 1

Metrik	Count	Mean	Std	Min	Max
likes	546.00	945558.79	755677.84	52000.00	7900000.00
comment	546.00	30035.39	44285.25	0.00	320900.00
shares	546.00	124136.91	201810.26	1357.00	2500000.00
plays	546.00	26.3 M	17.3 M	1.3 M	167.5 M
duration	546.00	75.33	206.86	0.00	1835.00
music_original	546.00	0.74	0.44	0.00	1.00

Based on the descriptive statistical results, Cluster 0 exhibited lower average values of likes, comments, shares, and plays, representing videos with low-to-moderate engagement. In contrast, Cluster 1 demonstrated significantly higher engagement values across all metrics, representing videos with high engagement performance or viral potential. In addition, the average video duration in Cluster 1 was slightly longer than that in Cluster 0. However, the difference was not substantial enough to influence the clustering process as strongly as the primary engagement variables. Meanwhile, the use of original music showed relatively similar proportions in both clusters, indicating that this variable was not a major distinguishing factor in the clustering process.

Overall, the clustering results demonstrate that the K-Means algorithm successfully grouped *#edukasi* TikTok videos into two main engagement characteristics based on user interactions on the TikTok platform.

3.5 Social Network Analysis (SNA)

The Social Network Analysis (SNA) stage was conducted to analyze the relationships between hashtags in the captions of educational video content on TikTok. Relationships between hashtags were analyzed based on the co-occurrence of hashtags within the same

content [15]. The transformed data in the form of Source, Target, and Weight columns were then modeled into a network structure (graph) using Gephi software. In the resulting network, each hashtag was represented as a node, while relationships between hashtags were represented as edges. The weight value indicated the frequency of two hashtags appearing together within a single video. This study uses an undirected graph because the relationships between hashtags were considered bidirectional.

Network visualization was performed using the ForceAtlas2 layout with the assistance of the LinLog Mode and Inverted Edge Weight features to clarify hashtag community structures. Furthermore, network evaluation was evaluated using metrics such as Average Degree, Average Weighted Degree, Degree, Weighted Degree, and Modularity to measure connectivity levels and community formation within the network [16]. The analysis results were examined separately for each cluster generated by K-Means. The network evaluation results for cluster 0 are shown in Table 9.

Table 9. Example of Network Evaluation Results of Cluster 0

Label	Degree	Weighted Degree	Modularity class	Size
#edukasi	21	1485	0	1
#edukasikesehatan	3	403	0	0.1
#faktaunik	6	407	1	0.25
#faktamenarik	6	377	1	0.25
#laguanak	4	295	2	0.15
#laguanakindonesia	2	135	2	0.05

Based on the Gephi analysis results, the network in Cluster 0 had an Average Degree value of 3.200 and an Average Weighted Degree value of 195.533, indicating that each hashtag was connected to approximately three other hashtags with moderate relationship strength. A modularity value of 0.448 indicates that the network formed relatively clear communities. The hashtag #edukasi had the highest Degree and Weighted Degree values compared to other hashtags, making it the main connectivity center within the Cluster 0 network. The network evaluation results for Cluster 1 are shown in Table 10.

Table 10. Example of Network Evaluation Results of Cluster 1

Hashtag	Degree	Weighted Degree	Modularity Class	Size
#education	2	407	0	0.125
#edukasi	4	512	0	0.375
#inspiration	2	352	0	0.125
#mainanedukasi	9	502	1	1
#mainananak	9	507	1	1
#edukasikesehatan	1	63	0	0

The network evaluation results for Cluster 1 are presented in Table 10. Based on the Gephi analysis, the network in Cluster 1 had an Average Degree value of 6.000 and an

Average Weighted Degree value of 356.588, indicating that hashtags in this cluster had higher connectivity levels compared to Cluster 0. A modularity value of 0.376 indicates that the network still formed several hashtag communities, although the resulting community structure appeared more centralized. In addition, higher Degree and Weighted Degree values observed in several nodes indicate stronger co-occurrence relationships among hashtags within the Cluster 1 network.

Interpretation was conducted by analyzing hashtag network visualizations in each cluster to identify relationship patterns among hashtags appearing in educational TikTok content. In the visualization process, only relationships with weight values above 40 were displayed to make the network structure clearer and easier to identify. The network visualization results for Cluster 0 are presented in Figure 5.

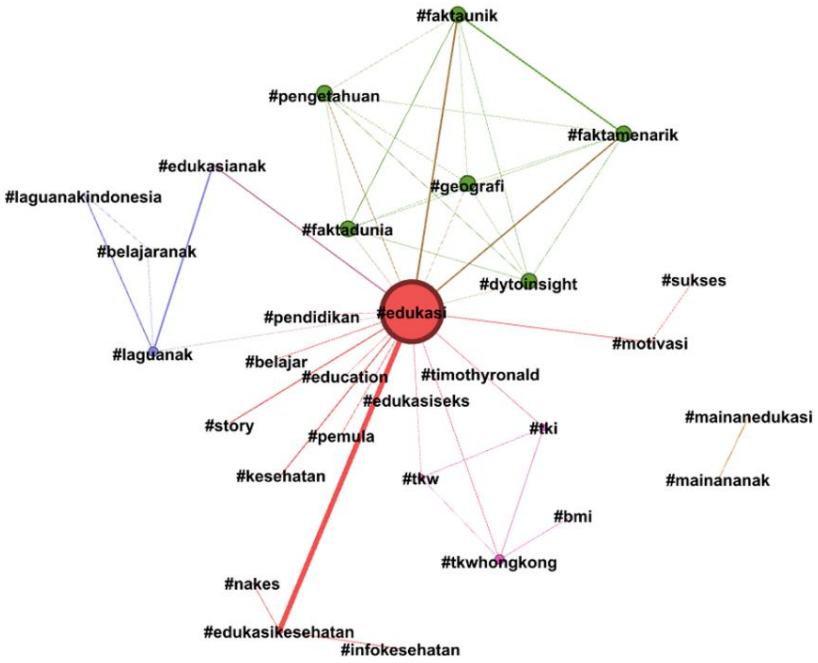


Figure 5. SNA Visualization of Cluster 0

In Cluster 0, the network structure appeared more dispersed with several smaller communities. The hashtag #edukasi became the central node with the most dominant connectivity and was connected to hashtags such as *#edukasikesehatan, #faktaunik, #faktamenarik, #laguanak,* and *#laguanakindonesia*. Several communities were identified, including health related communities such as #edukasikesehatan and *#kesehatan*, fact related communities such as *#faktaunik* and *#faktamenarik*, and children's education communities such as *#laguanak* and *#edukasianak*. However, relationships between communities remained relatively weak, causing the network to appear less dense. This pattern indicates that hashtag usage in Cluster 0 tended to be more diverse but had not yet formed strong topic relationships. The network visualization results for Cluster 1 are presented in Figure 6.

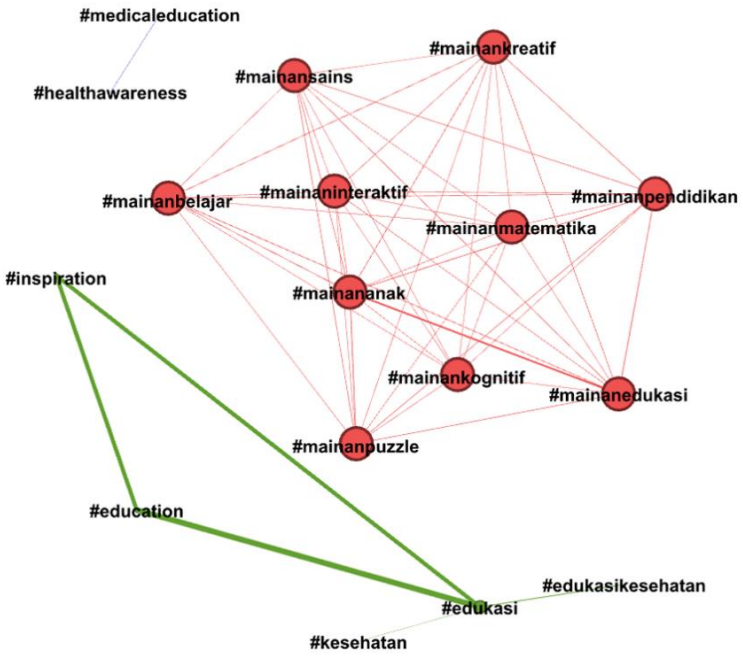


Figure 6 . SNA Visualization of Cluster 1

The hashtag *#edukasi* was connected to several hashtags such as #education, #inspiration, *#mainanedukasi*, *#mainananak*, and *#edukasikesehatan*. In addition, communities related to educational games were identified, including *#mainanbelajar*, *#mainankreatif*, and *#mainansains*, as well as education and health-related communities such as #education, #inspiration, *#kesehatan*, and *#edukasikesehatan*. Although only relationships with weight values above 40 were displayed in the visualization, the relationships among hashtags remained interconnected within a broader network structure. This denser network indicates that hashtags in Cluster 1 were more frequently used together and exhibited more consistent topic relationships, which aligns with the higher engagement characteristics observed in Cluster 1.

CONCLUSION

This study successfully analyzed engagement patterns of educational content on TikTok using a combination of K-Means Clustering and Social Network Analysis (SNA). The clustering results indicate that *#edukasi* content can be divided into two main groups, namely low engagement and high engagement clusters. In addition, the network analysis results show that each cluster has different hashtag relationship patterns. The low engagement cluster formed a more dispersed network structure, whereas the high engagement cluster exhibited a denser and more strongly connected hashtag network.

The results indicate that the combination of K-Means Clustering and SNA is effective for identifying engagement patterns and hashtag relationships in TikTok educational content. Future research could be expand by using larger datasets or incorporating additional analytical methods to gain a deeper insights into engagement patterns on social media platforms.

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