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Classification of Gen-Z Fashion Trends Based on Tiktok Social Media Activities Using the K-Means Clustering Method

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Abstract

Fashion trends continue to evolve along with changes in time, culture, and technology. Social media plays a significant role in disseminating these trends, especially among Generation Z (Gen-Z). This study aims to classify Gen-Z fashion trends based on their activities on TikTok using the K-Means clustering method. The data were collected through web scraping techniques from the TikTok platform, including variables such as the number of likes, comments, shares, saves, and fashion-related hashtags. Prior to clustering, the data were preprocessed through cleaning, normalization, and feature selection to ensure optimal clustering performance. The K-Means algorithm was then applied to group the data into clusters based on engagement patterns. The results show three main clusters: cluster 1 consists of posts with very high engagement and strong viral tendencies, often supported by major influencers; cluster 2 represents posts with moderate engagement, typically originating from medium-scale accounts; and cluster 3 includes posts with low engagement, generally reflecting casual styles with limited audience interaction. Overall, the findings indicate that Gen-Z fashion trends on social media are strongly influenced by visual appeal, influencer involvement, and interactive content elements.

Keywords: *fashion trends, Generation Z, K-Means clustering, TikTok, web scraping*

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1. Introduction

Fashion trends continue to evolve along with changes in time, culture, and technology. Social media plays a significant role in spreading these trends, especially among Generation Z (Gen-Z). TikTok, as one of the most popular social media platforms, has a strong influence on shaping the fashion preferences and lifestyles of Gen-Z users. The use of TikTok affects Gen-Z's consumptive behavior in both fashion and lifestyle, while financial literacy may mitigate its negative impacts [1]. Platforms such as TikTok, Instagram, and YouTube accelerate the adoption of global trends, making Gen-Z's dressing patterns more dynamic and unique as a form of self-expression and identity. The "TikTok phenomenon" also illustrates how fashion content such as unboxing videos, product reviews, and fashion tutorials influences consumer preference [2]. Therefore, understanding fashion trends through TikTok activities is essential to identify changes in fashion styles more accurately.

Despite the growing body of research on social media-driven fashion trends, there is still a limited number of studies that specifically analyze Gen-Z fashion trends based on engagement patterns on TikTok. Previous studies generally focus on broader aspects such as consumer behavior, purchasing decisions, or trends across multiple platforms, without deeply exploring interaction-based metrics such as likes, comments, shares, and saves. In addition, few studies have applied clustering techniques to classify fashion trends using TikTok-specific data, particularly in the context of developing countries or specific local regions. This indicates a clear research gap in understanding how engagement metrics can be used to systematically categorize fashion trends among Gen-Z users.

Clustering is one of the important techniques in data mining, which serves to group data into subsets that have similarities based on certain characteristics or patterns [3]. This technique is used not only to group data, but also to identify information that has certain characteristics, making further analysis easier

[4]. Compared to other clustering methods, K-Means is computationally efficient and suitable for large-scale social media data, making it highly relevant for analyzing TikTok datasets that contain high-volume and dynamic user interactions. One of the widely used clustering methods is K-Means Clustering, which is a non-hierarchical data clustering method that aims to divide data into several groups, where each group contains data with characteristics similar to each other but different from other groups [5].

The K-Means Clustering method has been used in various studies to analyze fashion preferences based on consumption patterns and interactions on social media [6]. Based in research [7] examined the influence of fast fashion on thrifting trends, finding that consumers are divided into two groups with different consumption patterns, influenced by price factors, trends, and sustainability awareness. Meanwhile, [8] applied a similar method in the hijab industry, categorizing products based on purchasing patterns and customer preferences, showing that certain designs and colors are more desirable in e-commerce. These two studies prove the effectiveness of K-Means in identifying hidden patterns in dress preferences, which the fashion industry can leverage for marketing strategies, promotion personalization, and trend analysis, especially among Gen Z who are active on social media. Therefore, this study aims to classify Gen-Z fashion trends based on TikTok engagement metrics using the K-Means clustering method. The novelty of this research lies in 1) the use of TikTok-specific interaction data (likes, comments, shares, saves, and hashtags), 2) the focus on Gen-Z behavioral patterns in digital fashion consumption, and 3) the application of clustering techniques to identify hidden patterns in social media-driven fashion trends. The results of this study are expected to provide deeper insights into how fashion trends evolve in the digital era and serve as a reference for researchers, marketers, and the fashion industry.

2. Theoretical Reviews

2.1 Clustering

Clustering is one of the important techniques in data mining, which serves to group data into subsets that have similarities based on certain characteristics or patterns. This technique is used not only to group data, but also to identify information that has certain characteristics, making further analysis easier [9]. Clustering analysis aims to group objects with similar characteristics into one group, while objects with different characteristics are placed in another group [10]. This process seeks to maximize similarity within a group and minimize similarity between groups. There are several methods that can be used in clustering analysis, including partition-based clustering and hierarchical clustering, which are the two main approaches in this technique [11].

2.2 K-Means Clustering

The k-means algorithm relies on the value of k, which always has to be determined to perform cluster analysis. Clustering with different k values will ultimately produce different results [12]. The various initialization problems analyzed in recent studies do not consider the problem where the algorithm only converges to a poor local minimum. K-means clustering is a non-hierarchical data clustering method that aims to group data into one or more clusters. With this approach, data that has similar characteristics will be grouped into the same cluster, while data that has different characteristics will be placed in another cluster.

The K-means algorithm is a widely used clustering method that partitions data into k clusters based on similarity, where k represents the number of groups to be formed. The algorithm works by minimizing the distance between data points and their respective cluster centroids, thereby maximizing intra-cluster similarity and minimizing inter-cluster similarity[13]. However, K-means has several limitations. The algorithm is sensitive to the initial selection of centroids, which may lead to convergence at a local minimum rather than a global optimum. In addition, K-means requires the number of clusters (k) to be determined in advance, which can influence the final clustering results. The method is also sensitive to differences in data scale, making normalization an important preprocessing step. Furthermore, the presence of outliers can significantly affect the cluster formation and reduce the accuracy of the results.The

K-means algorithm requires an input parameter called k, which is used to divide a set of n objects into k clusters. The goal of this clustering is to maximize the degree of similarity between members in one cluster and minimize the similarity with members from other clusters. The similarity of members to the cluster is measured based on the proximity of the object to the average value in the cluster, known as the cluster centroid or center of mass [14]. Despite these limitations, K-means remains suitable for this study due to its computational efficiency and ability to handle large-scale datasets. This makes it particularly appropriate for analyzing TikTok data, which is characterized by high volume, dynamic interactions, and diverse user engagement patterns.

2.3 Trends in How to Fashion

Fashion trends are a phenomenon that continues to develop along with the changing times, influenced by economic, social, and technological advances. The word “trend” itself comes from the term “trend,” which refers to something that is popular in a certain period [15]. In the world of fashion, students are one of the groups that actively follow trends, especially due to the increasingly massive exposure to social media and globalization. The fast fashion phenomenon also contributes to encouraging students to follow viral styles, although these trends often only last for a short time. In addition, the economic aspect also influences the fashion preferences of students, who are now turning to thrift shops as a more affordable and sustainable alternative [16].

TikTok a creative video creation app launched in September 2016 by ByteDance, has become one of the most popular social media platforms in Indonesia, with the number of active users reaching around 50 million, placing Indonesia as the country with the fourth largest number of TikTok users in the world [17].. This phenomenon is closely related to the trend of “Racun TikTok,” where fashion content such as unboxing, product reviews, and fashion tutorials are in high demand, especially by female users [18]. The hashtag #racuntiktok has reached more than 2 billion impressions, reflecting the high enthusiasm of users for the trend. This phenomenon also contributes to increased consumptive behavior, especially among millennials, who tend to be easily influenced by fashion trends that develop on social media .

Some of the categories of fashion trends popular among students reflect the diversity of tastes and dressing styles. The Fashion Scene, for example, features styles inspired by indie and punk music culture, with accessories such as pins, leather bracelets, and boots giving off a rebellious and expressive vibe. Streetwear fashion is more prominent with casual yet stylish styles, often featuring well-known brands, oversized hoodies, and limited edition sneakers that reflect an urban and modern style. Casual Fashion emphasizes comfort and simplicity, with options such as plain t-shirts, jeans and denim jackets that are suitable for everyday activities [19]. Meanwhile, Fashion Vintage highlights retro styles from the 70s to 90s, with unique patterns, muted colors, and classic materials that give a nostalgic feel. Lastly, Fashion Y2K features futuristic and colorful styles inspired by the 2000s, with elements such as metallics, neon colors, and bold accessories that reflect confidence and creativity. This diversity of styles shows that fashion trends do not only follow the flow of popularity, but also become a form of self-expression for students.

Fashion trends have a significant influence on students, especially in social and psychological terms. The majority of students follow trends because of the encouragement of the social environment and the desire to always look attractive [20]. In fact, some students experience Fear of Missing Out (FOMO), which is the fear of being left behind by the latest trends so they tend to follow fashion changes quickly. This shows that fashion trends are not just about appearance, but also have an impact on students' behavior and consumption patterns in everyday life.

3. Methods

3.1 Type of Research

This research uses a quantitative approach with an exploratory method that aims to identify and cluster Gen-Z fashion trends based on their activities on TikTok social media. The method used is K-Means clustering, which enables the classification of dressing styles based on users' interaction patterns with fashion content on TikTok.

3.2 Data Source

The data used in this research is secondary data obtained from the TikTok social media platform. The data is collected through web scraping techniques to retrieve information about emerging fashion trends. The data collected includes video ID, author name, number of likes, number of comments, number of shares, number of saves, and hashtags used in fashion-related videos. Data collection is done using web scraping techniques to obtain information about trending fashion videos on TikTok.

3.3 Research Variables

The research variables used in this study are:

a. Number of interactions (likes, comments, shares and saves) on fashion videos.
b. Frequency of use of fashion-related hashtags (such as #skena, #streetwear, #casual, #vintage, #y2k, etc.).

3.4 Data Analysis Technique

Data analysis in this study was conducted through several systematic steps, including data preprocessing, determining the optimal number of clusters, and applying the K-means clustering algorithm.

1. Data Preprocessing

Before performing clustering, the dataset was preprocessed to ensure data quality and improve the accuracy of the results. The preprocessing steps included:

a. Data Cleaning

Incomplete, duplicate, or irrelevant data were removed to ensure the dataset was consistent and reliable.

b. Feature Selection

Relevant variables were selected, including the number of likes, comments, shares, saves, and fashion-related hashtags, which represent user engagement on TikTok.

c. Data Transformation and Normalization

Since the variables have different scales, normalization was applied using the Min-Max normalization method to transform the data into a comparable range. This step is important because K-means is sensitive to differences in data scale.

d. Outlier Handling

Outliers were identified using statistical approaches (e.g., Z-score or IQR method) and handled by either removing extreme values or adjusting them to reduce their impact on clustering results.

2. Determining the optimal number of clusters with the Elbow method

The optimal number of clusters is determined using the Elbow method by visualizing the Within-Cluster-Sum of Squares (WCSS) value against the number of clusters. The "elbow" point on the graph indicates the optimal number of clusters. The SSE formula is [20]:

$$SSE = \sum_{k=1}^{k} \sum_{x_i \in Ck} (x_i - \varphi_k)^2 \tag{1}$$

with:
C_k = k Cluster
k = number of Cluster

x_i = the i-th data point
φ_k = centroid of the k-th cluster

3. Perform Clustering with K-Means algorithm

   K-Means algorithm is a clustering method that partitions data into several groups (clusters) based on the similarity of data characteristics. The steps of the K-Means algorithm are as follows:
   a) Determine the value of K as the number of clusters to be created.
   b) Randomly determine the initial cluster center point (K centroid).
   c) After getting the cluster center point, the next step is to calculate the distance of each data to each centroid by using the correlation formula between two object, such as seen in the Euclidean Distance Formula [21]:

$$\boldsymbol{D_i(x_1, x_2) = \sqrt{\textstyle\sum_{j=1}^{p}\left(x_{2j} - x_{1j}\right)^2}} \qquad (2)$$

   with:
   D_i = The distance between the i-th and j-th data points
   x_{1j} = Data coordinates x_1 in dimension j
   x_{2j} = Data coordinates x_2 in dimension j and P data dimensions

   After obtaining the results of calculating the distance for each data point, the next step is to group the data based on the closest distance between each data point and the cluster. A new centroid is then determined by calculating the average value of the data within each similar cluster, and this calculation can be performed using the following equation [22]:

$$\boldsymbol{V_{ij} = \frac{\sum_{j=1}^{p} x_{kj}}{N_i}} \qquad (3)$$

   with:
   V_{ij} = Value of the j-th column for the i-th cluster
   x_{kj} = Value of the j-th column for the k-th data point
   N_i = Number of data points in the i-th cluster

4. Analyzing the clustering results

   The clustering results were analyzed by reviewing the patterns formed within each cluster. Summary statistics (such as average likes, comments, shares, and saves) are calculated for each cluster using the aggregate() function.

5. Visualizing the clustering result

   The clustering results are visualized in the form of a scatter plot using the fviz_cluster( ) function from the factoextra package. This visualization shows the distribution of the data in a two-dimensional space, with the points colored based on their clusters

6. Save and display clustering results

   The clustering results are saved into a CSV file for documentation and further analysis. The saved data includes the original data along with the Cluster column indicating the cluster for each observation. The clustering results are also displayed in the console for immediate inspection.

7. Summarize the analysis results

   Based on the clustering and visualization results, this research concludes Gen-Z's fashion trends and how interactions on TikTok influence their fashion consumption. The insights gained can be used to understand Gen-Z's behavior patterns in consuming fashion content on social media.

With this method, the research is expected to provide deeper insights into the influence of TikTok activities on clothing trends among Gen-Z and how their fashion consumption patterns can be classified based on interactions on social media.

4. Results and Discussion

The preliminary summary of the collected dataset regarding Gen-Z fashion trends on TikTok is presented in Table 1

Table 1. Preliminary Data on Gen-Z Fashion Trends

No	Username	Likes	Comments	Shares	Saves	Category
1	ig mhmdalpiinn	180600	1411	5325	12800	Skena
2	ig : _rizaldicp	74800	507	2767	4591	Skena
3	ig : _rizaldicp	8126	182	244	526	Skena
4	ig : mhmdalpiinn	149900	1654	3596	10800	Skena
5	ig : mhmdalpiinn	175500	650	1950	8628	Skena
…	…	…	…	…	…	…
250	y2ktentacion	315400	797	3085	3800	Y2K

Based Table 1 presents preliminary data on Gen-Z fashion trends collected from TikTok user activities, with key variables including the number of likes, comments, shares, and saves as indicators of engagement levels. The data show that each post has varying levels of interaction, where some accounts, such as igmhmdaIpiinn and y2ktentacion, exhibit high numbers of likes and saves, indicating strong popularity and audience interest. The categories identified, such as Skena and Y2K, represent different fashion trends emerging among Gen-Z users. The variation in engagement values across posts suggests differences in how audiences respond to each trend, which provides a meaningful basis for clustering analysis. Overall, this dataset indicates that Gen-Z fashion trends on TikTok can be effectively analyzed based on engagement metrics, enabling the grouping of trends into clusters with similar interaction characteristics.

The data that has been collected is then optimized using the elbow method to determine the best number of clusters. The following are the results of the SSE calculation based on testing the value of k = 2 to k = 10.

Table 2. SSE Calculation Results for each Cluster

No.	Result SSE	difference
1	550,55044	0
2	177,53360	373,01684
3	127,33199	50,20161
4	105,08901	22,24298
5	80,39084	24,69817
6	74,24477	6,14607
7	69,26766	4.97711
8	67.21054	2.05712
9	53.89062	13,31992

From the SSE calculation of the Elbow method in Table 2, it is found that the SSE value that has the largest difference is at the k = 3 value, so the optimal number of clusters that can be formed is 3 clusters.

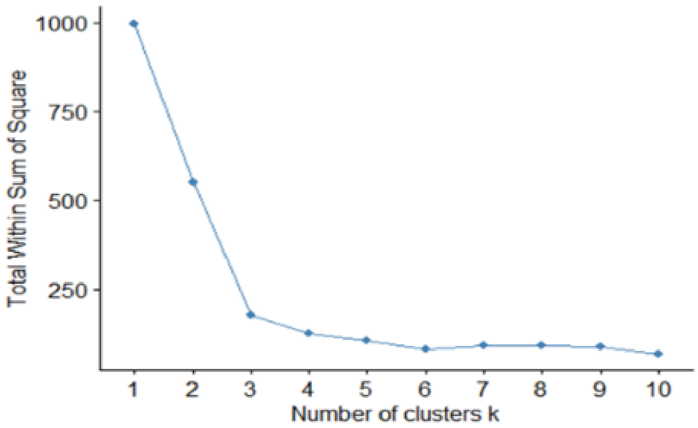

Figure 1. SSE Graph of Elbow Method

Based on the SSE graph using the Elbow method in Figure 1, it can be observed that the most significant decrease in SSE occurs at k=3, indicating a potential optimal number of clusters. After this point, the reduction in SSE becomes more gradual, suggesting diminishing returns for adding more clusters. The Silhouette Score was calculated to measure the cohesion and separation of clusters, where a higher value indicates better-defined clusters. In addition, the Davies-Bouldin Index (DBI) was used to evaluate cluster quality, where a lower value represents better clustering performance.

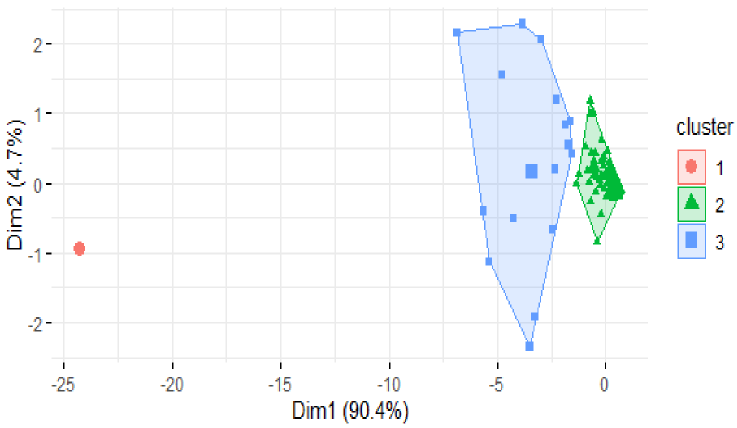

Figure 2. Clustering Results

Figure 2 shows the results of K-Means clustering for classifying Gen-Z fashion trends based on TikTok activities. The visualization uses Principal Component Analysis (PCA), where Dim1 (90.4%) explains most of the variance and is mainly influenced by engagement variables such as likes, comments, shares, and saves. Dim2 (4.7%) captures smaller variations, providing additional differentiation in user interaction patterns. The results identify three clusters: Cluster 1 (red) represents highly viral content with extreme engagement, Cluster 2 (green) reflects stable and mainstream trends with moderate engagement, and Cluster 3 (blue) indicates more variable or emerging trends. The clear separation between clusters confirms that engagement metrics effectively distinguish fashion trend patterns, supporting the suitability of K-Means for this analysis.

Table 3. Clustering Results Using Elbow Method and K-Means Clustering Algorithm

***Cluster* Model**	
***Cluster* 1**	1 data
***Cluster* 2**	232 data
***Cluster* 3**	17 data
Total Data	250 data

Table 3 shows the distribution of data for k=3, which is highly imbalanced. Cluster 1 contains only 1 data point, Cluster 2 has 232 data points, and Cluster 3 includes 17 data points out of 250 observations. This indicates that most data are concentrated in Cluster 2, representing the dominant engagement pattern. The single-member Cluster 1 indicates the presence of an outlier with extremely high engagement. Instead of being removed, this data point is retained as it represents rare but important viral content. Therefore, the imbalance reflects the natural variation in TikTok engagement patterns rather than a modeling error.

Table 4. Clustering Results Cluster **1**

No	Username	*Likes*	Comments	*Shares*	*Saves*	Category
1	Abah Usur	2700000	28600	162100	180900	Skena

Table 4 is the grouping result of cluster 1 which has 1 username member. These results contain posts with very high engagement and tend to go viral. Posts in this cluster get millions of likes, tens of thousands of comments, and hundreds of thousands of shares and saves. The dominating trend in this cluster is the scene style, which seems to have strong visual appeal and is often associated with global trends. Many of these posts come from accounts with large followings, including influencers or celebrities, which makes it easier for them to spread widely. In addition, the content in this cluster is likely to have elements that encourage interaction, such as challenges, unique concepts or links to emerging popular phenomena.

Table 5. Clustering Results of Cluster 2

No	Username	*Likes*	Comments	*Shares*	*Saves*	Category
1	ig : mhmdalpiinn	180600	1411	5325	12800	Skena
2	ig : _rizaldicp	74800	507	2767	4591	Skena
3	ig : _rizaldicp	8126	182	244	526	Skena
…	…	…	…	…	…	…
232	y2ktentacion	315400	797	3085	3800	Y2K

Table 5 is the grouping result of cluster 2 which has 232 usernames. The results show that engagement is quite high, but not as viral as cluster 1. Although the number of likes, comments, shares, and saves is quite large, it does not reach a very massive scale. Like cluster 1, the dominant fashion trend in this cluster is scene style, but with a lower level of engagement. Posts in this cluster are likely to come from medium-sized accounts, which, while having a sizable audience, are not as popular as the large influencers in the viral cluster. The content in this cluster remains interesting, but may lack the factors that make it explode on social media, such as a boost from an algorithm or a very strong trending element.

Table 6. Clustering Results of Cluster 3

No	Username	*Likes*	Comments	*Shares*	*Saves*	Category
1	rzkgii	529800	1765	9417	30100	Skena
2	this_Evan10	552100	9366	37700	36500	Skena
3	ig : andrianrhmt	388000	2886	4589	25900	Sekna
…	…	…	…	…	…	….
17	***Shyy*** 👸	805500	7236	22100	18030	Y2K

Table 6 is the clustering result of cluster 3 which has 17 usernames. The results show that posts with low to moderate engagement, where the number of likes, comments, shares, and saves are relatively small compared to other clusters. Dress trends in this cluster are dominated by casual styles, which although widely used, do not seem to attract much attention on social media. Posts in this cluster are likely to come from small accounts or individuals who do not have a large following, hence limited dissemination. Also, the content tends to lack elements that can encourage further interaction, such as interesting captions or viral trends.

5. Conclusion

This research provides a quantitative framework for understanding Gen-Z dressing trends on social media, moving beyond descriptive observations to offer actionable insights into engagement patterns. The K-Means clustering highlights three distinct tiers of user interaction: highly viral "scene" trends amplified by major influencers in Cluster 1; moderately engaging content from medium-sized accounts in Cluster 2; and casual styles lacking interactive elements that result in the lowest engagement in Cluster 3. A key contribution of this study is empirically demonstrating that visual aesthetics, interactive content elements, and influencer presence are the primary drivers of content success, equipping fashion industry stakeholders and content creators with a strategic basis to optimize their social media strategies. However, this study is limited by its exclusive focus on TikTok data and quantitative engagement metrics within a specific timeframe. Future research should consider cross-platform comparisons and qualitative sentiment analysis to establish a more comprehensive understanding of Gen-Z fashion dynamics.

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