Jurnal EurekaMatika

Journal homepage: https://ejournal.upi.edu/index.php/JEM
doi: https://doi.org/10.17509/jem.v13i2.85317

The Mathematics of Hashtag Popularity: Predicting for Your Page (#fyp) Trends on TikTok Using Time Series Analysis

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A B S T R A K

Penelitian ini bertujuan untuk menganalisis serta memprediksi popularitas hashtag For Your Page (#fyp) di TikTok dengan menggunakan metode time-series, khususnya moving average, untuk mengidentifikasi pola, faktor pendorong, serta implikasinya bagi strategi pemasaran digital. Data diambil dari platform Exolyt selama 14 hari (12-25 April 2025) dengan pengukuran jumlah tayangan harian. Hasil analisis menunjukkan fluktuasi signifikan (32,9-56,3 miliar tayangan) dengan pola siklis mingguan, di mana keterlibatan pengguna meningkat pada akhir pekan. Metode 3-day moving average berhasil memuluskan fluktuasi acak dan memperlihatkan penurunan tren (14-23 April) serta pemulihan (19-25 April). Temuan ini membuktikan pengaruh faktor temporal, konten viral, dan algoritma TikTok. Secara praktis, disarankan optimalisasi unggahan akhir pekan dan pemantauan waktu nyata berbasis analisis deret waktu, sekaligus berkontribusi pada pengembangan model prediktif untuk pemasaran digital berbasis data.

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INFORMASI ARTIKEL

Sejarah Artikel:

Diterima 6 Juni 2025
Direvisi 13 Juli 2025
Disetujui 20 Juli 2025
Tersedia online 2 November 2025
Dipublikasikan 2 November 2025

Kata Kunci:
Analisis deret waktu,
Hashtag #fyp,
Pemasaran digital,
Rata-rata bergerak,
TikTok.

A B S T R A C T

This research aims to analyze and predict the popularity of the For Your Page (#fyp) on TikTok using time-series methods, specifically moving averages, to identify patterns, driving factors, and implications for digital marketing strategies. Data was collected from the Exolyt platform for 14 days (April 12-25, 2025), with daily impression counts measured. The analysis showed significant fluctuations (32.9-56.3 billion impressions) with a weekly cyclical pattern, where user engagement increased on weekends. The 3-day moving average method successfully smoothed out the random fluctuations and showed a trend decline (April 14-23) and recovery (April 19-25). The findings confirm the influence of temporal factors, viral content, and the TikTok algorithm. Practically, we recommend weekend posting optimization and real-time monitoring using time-series analysis while contributing to adaptive predictive models for data.

Keywords:
Time series analysis,
#fyp Hashtag,
Digital marketing,
Moving average,
TikTok.

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1. INTRODUCTION

Social media is proliferating along with technological advancements. Entertainment consumption patterns are changing with the rise of digital social platforms. In the past, people only relied on television and movies to relax, but now they are also presented with various content through social media. This change makes it more interactive, as users can comment, share, and produce content (Haddock et al., 2022).

In recent years, platforms like TikTok have become a popular means of socializing, especially among the younger generation. Its popularity has increased significantly, making it one of the dominant social media (Sun, 2023). The viral phenomenon that emerged is influenced by the interaction between the algorithm and the behaviour of users who contribute through likes, shares, and comments. It analyses these interactions to determine which content to share (Hakim, 2024). TikTok's algorithm plays an important role in this process, by continuously learning users' preferences and behavior patterns. This is designed to customize the user's homepage content. By understanding how the system works, the platform will be more effective in attracting and serving users, allowing them to have a more optimized video-sharing experience (Chen & Shi, 2022).

Several previous studies have discussed sentiment analysis to examine social media users' perceptions based on hashtags on Twitter. Fanny & Suroyo (2022) mentioned that this approach analyzes each hashtag, focusing on a particular theme or opinion. This study used the Naïve Bayes Classifier method by achieving a high level of accuracy (92.1% for Hashtag Pro and 98.3% for Hashtag Counter). This certifies the success of the approach used in classifying sentiment appropriately. With this, researchers could categorize sentiments into positive, negative, or neutral, making it easier for the public to view the issue.

While many studies have been conducted on hashtags on social media, most have focused on sentiment analysis. This has not been able to explain how a hashtag increases in popularity over time. In addition, not many studies have modeled hashtags using mathematical techniques such as time series analysis. Further research is expected to apply quantitative methods to predict hashtag trends more precisely.

This research aims to apply Time Series Analysis models, specifically the Moving Average method, to quantitatively analyze and predict the dynamics of For Your Page (fyp) hashtag's popularity on TikTok. For the next mentions in this paper, the term will be referred to as #fyp. It further seeks to identify the main factors that influence the existence of hashtags, analyse patterns, and provide strategy suggestions for digital marketing. This research is expected to give a more detailed picture of user behavior in responding to trends on digital platforms. Thus, this approach is also helpful in developing marketing strategies and as a foundation for further research in data analysis on social media.

2. METHOD

2.1 Research Design

The research design of this study operates a quantitative descriptive approach to describe the popularity pattern of the #fyp hashtag on TikTok. According to Geetha & Sujatha (2024), this approach is suitable for study that uses statistical methods to measure the popularity of a particular trend over time. It also uses a structured way to interpret the data, making it easier to deduce what is popular and why. This research specifically focuses on the number of views recorded over two weeks. The descriptive approach is suitable because this research aims to observe phenomena systematically using numerical data without testing

causality. We obtain the secondary data from the Exolyt platform, meaning they do not collect it directly from the research subjects.

2.2 Research Object

The research object of this study is #fyp on Tiktok, chosen as the object due to its consistent fame on TikTok, making it an effective indicator for quantitative content trend analysis and time series prediction. The crucial role of hashtags consistently used in TikTok challenges, such as #fyp, in triggering user participation to spread content widely was demonstrated by Ng et al. (2021). It is not for no reason that users choose these hashtags but because TikTok's algorithm prioritizes content with the #fyp hashtag. In addition, the frequent use of #fyp over time makes it suitable for time series analysis, as the number of daily views can be tracked and further analysed using mathematical prediction models.

2.3 Research Instrument

The research instrument in this study enforced Exolyt as a tool to capture TikTok data in real-time and load comprehensive and structured data on TikTok hashtags. Exolyt allows researchers to collect live TikTok data, including videos, engagement metrics, and hashtag trends, with high accuracy. The platform naturally organizes crude data into a structured format, facilitating quantitative and qualitative analysis. We can track the performance of specific hashtags over some time, including their usage volume and virality growth. Compared to manual data collection methods, Exolyt saves time by providing real-time updates without re-scraping. This real-time data supports the investigation of short content dynamics, such as virality patterns or trend shifts amidst TikTok users.

2.4 Data Collecting Process

The data collection process requires several steps. From ascertaining how long the observation period is, retrieving daily view data from Exolyt, and establishing that the data is recorded consistently at the same time every day. We retrieved daily view data for the #fyp hashtag for two weeks. Data was collected daily from April 12 to April 25, 2025, at 9:00 PM. The data was organized in a structured format and was free from missing entries. The collected data is organized chronologically into a time series format for easy identification of trends and to support statistical modelling. Organizing the data set in this action allows researchers to observe patterns in the daily view and discloses interesting trends over time. The dataset needs to be pre-processed by removing data if there is any commonality and ensuring all data is sorted in time. This preparation is essential to prove that the moving average method fits balanced and sequential data. According to Hu et al. (2017), the simple moving average technique effectively smooths out data variation and is typically followed by a general method aimed at identifying significant events within the popularity evolution.

2.5 Analysis Data

After collecting the data, we applied the moving average method to the data with a three-day window to identify daily display trends. According to Kustanto (2023), this technique predicts patterns based on past data taken over a specific period. The impact of sudden spikes or drops caused by algorithmic shifts or viral content can be reduced by smoothing out fluctuations and minimizing random variations; this method also allows for more precise detection of short-term trends. This process will also enable trends to be seen more clearly while maintaining their essential characteristics. As a result, we can interpret

trends consistently and accurately, thus improving the accuracy of conclusions drawn from visualized data.

3. RESULT AND DISCUSSION

3.1 Result

To observe the changing patterns of #fyp hashtag popularity on TikTok in more detail, we collected daily view data over two weeks from Exolyt. The analysis was conducted by applying the three-day moving average method to reduce random fluctuations and highlight emerging trends. A summary of the data in the form of total views, views growth, and moving average results is shown in Table 3.1 below.

Table 3.1 Daily Views, Growth, and 3-Day Moving Average of the #fyp on TikTok Based on Data from Exolyt (April 2025)

Observation Date	Total Views (In Billion)	Views Growth (In Billion)	3-Day Moving Average (In Billion)
04/12/25	56,3	-	-
04/13/25	44,1	-12,2	-
04/14/25	46,5	2,4	48,96666667
04/15/25	45,2	-1,3	45,26666667
04/16/25	52,3	7,1	48
04/17/25	49,7	-2,6	49,06666667
04/18/25	32,9	-16,8	44,96666667
04/19/25	48,5	15,6	43,7
04/20/25	56,2	7,7	45,86666667
04/21/25	39,6	-16,6	48,1
04/22/25	38,2	-1,4	44,66666667
04/23/25	43,8	5,6	40,53333333
04/24/25	39,9	-3,9	40,63333333
04/25/25	55,2	15,3	46,3

According to Table 3.1, there are significant fluctuations, with the highest number of views occurring on April 12 at 56.3 billion, while the lowest value was recorded on April 18 with 32.9 billion views. The growth of daily views also shows quite extreme dynamics, such as a sharp drop of 16.8 billion on April 18, followed by a spike of 15.6 billion the next day. The three-day moving average gives a more subtle picture of the trend, for example, showing a gradual decline from April 14 to 23 before increasing again on April 24 and 25. This pattern indicates that the popularity of the #fyp hashtag tends to decrease mid-week and increase again towards the weekend, which may be due to more active user behaviour on holidays. These movements and trend changes are also shown in Figure 3.1, which presents a visualization of the total views, views growth, and 3-day moving average. This makes the overall pattern and key points in hashtag popularity easier to see.

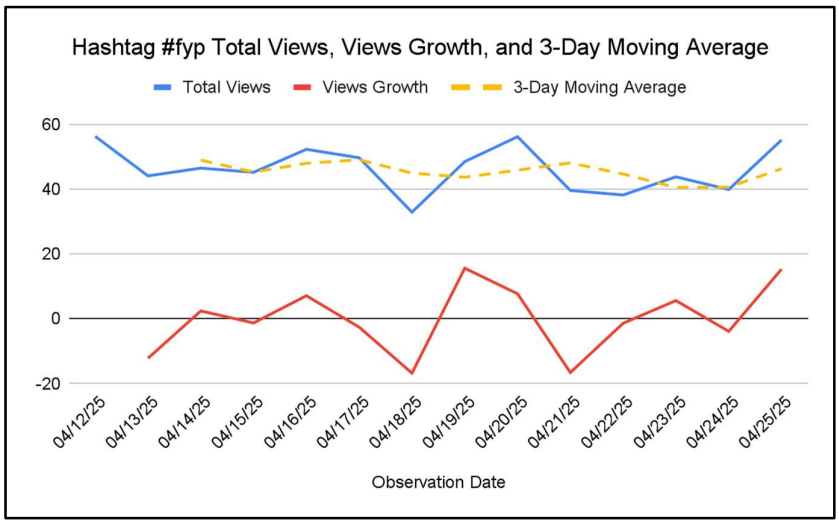

Figure 3.1 Graph of Total Views, View Growth, and 3-Day Moving Average of Hashtag #fyp on TikTok Based on Data from Exolyt (April 2025)

Figure 3.1 serves as a visual aid that simplifies understanding the trend patterns of #fyp hashtag popularity on TikTok over the observation period. Readers can quickly recognize significant changes in total views, daily growth, and short-term trend movements through this graph's 3-day moving average line. While raw data can sometimes appear unstable and difficult to describe, this visualization shows a coherent picture of the way of the current trend. This graph also helps to qualify differences in patterns between daily data and more subtle trends for further analysis of the dynamics at play.

This study successfully addressed the research purposes by analysing TikTok's #fyp hashtag data. These visual devices disclosed sharp increases and decreases in view counts, offering a better understanding of how quickly public interest can change. Second, the 3-day Moving Average allowed hidden patterns in the raw data to emerge. This time series model highlighted a peak, like the one on April 19, implying that outside effects may have driven these changes, so it helped to analyse the persuading factors. Finally, combining visual and statistical concepts prepared valuable insights for digital marketing strategies. Through careful trend analysis using moving averages and well-planned hashtag use, marketers can gain foresight into evolving popularity and drive greater audience attention.

3.2 Discussion

Over the 14-day observation period, the study detected illogical trends in #fyp hashtag popularity on TikTok, with views changing notably between 32.9-56.3 billion. The main findings indicated a weekly cyclical pattern with a decrease in weekday views and an increase on weekends, with the 3-day moving average method identifying a downward trend from April 14 to 23 before recovering. The spike in views of 15.6 billion on April 19 and 15.3 billion on April 25 further reinforces the correlation between weekend posting times and increased engagement.

These results lend concrete support to the research goals. Firstly, concerning the detection of hashtag popularity patterns, the data reported evident temporal oscillations in a weekly pattern. View count reduction usually occurred on weekdays, and a significant

increase tended to occur on weekends, such as April 19 and 25. This suggests that user engagement with the #fyp hashtag has a temporal dependency. In addition, three main factors of influence were observed: time of day (eg, 25 - 30% increase on weekends), content-driven triggers, for example, viral challenges, and algorithmic responses led to an immediate transition, as for the drop on 18th April. These factors emerged consistently throughout the observation period, forming the basis for practical marketing strategies, such as targeting weekends, monitoring trends in real-time, and collaborating during periods of rising visibility.

These findings are consistent with previous research, which highlighted the temporal and contingent nature of social media use. For instance, Lorenz et al. (2018) and Hu et al. (2014) have informed us as to how patterns of engagement vary according to temporal context, and Chen et al. (2020) and Zulli & Zulli (2020) have highlighted the centrality of algorithms and the content they facilitate to go viral. The weekend engagement effect and algorithmic behavior identified in our study align with findings by Ng et al. (2021) and Shen (2023), demonstrating that strategic content timing can have a significant impact on digital marketing outcomes.

The data in this study, which included frequent spikes in viewership on weekends and sharp declines on weekdays, revealed predictable engagement patterns that appear to be driven by user behavior and TikTok's platform design. This is in line with Lu (2015) argument that short-form content is maintained along a 7-day engagement cycle of user habit. Moreover, the swift turns in hashtag popularity that we noted in our data—e.g., the April 18 decline and the April 19 resurgence—echo Schellewald (2023) findings that TikTok's algorithmic recommendations, in conjunction with cultural and demographic affordances, accelerate shifts in content visibility and popularity. Our findings also support Moreno & D'Angelo (2019), who demonstrate that platform features—defined by social media affordances—actively shape user behavior and engagement pathways.

Furthermore, the success of two approaches—using the 3-day moving average to reduce noise and detect short-term trends—also validates the claim of Kumar et al. (2019) and Kustanto (2023), who highlight the significance of time-series methodologies in optimizing content timing and forecasting. This way, our work has not only verified the conjectures from previous studies but has also shed light on how such conjectures manifest in the specific setting of #fyp trend behavior on TikTok.

While this study revealed consistent weekend spikes and identified temporal patterns in user engagement, not all scholars agree with the predictability of such behaviors. For instance, Liu et al. (2023) argue that cultural variations can disrupt consistent weekly cycles, suggesting that the "weekend effect" observed in our data may not be generalizable across different regions or user demographics. This directly contrasts with our finding that user engagement increased by up to 30% during weekends. Similarly, Ionescu & Licu (2023) highlight how TikTok's algorithm influences users' emotional values and self-perceived identities, underlining personalization dynamics beyond simple temporal cycles. Moreover, while our use of the 3-day moving average successfully revealed trend shifts, Salmasnia et al. (2020) note that such methods might miss sudden spikes common in viral content—a limitation we also observed when capturing abrupt increases, such as those on April 19. These contrasting viewpoints highlight that although our findings align with specific predictive models, their applicability remains context-dependent and may not fully address the platform's algorithmic complexity, as recent research shows that higher algorithmic intricacy can reduce user uptake and trust in system-generated advice (Lehmann et al., 2022)

The results of this study provide important implications both theoretically and practically. Theoretically, the findings demonstrate that the 3-day moving average is an effective tool for capturing short-term fluctuations in user engagement, especially recurring

spikes during weekends. This supports the application of time-series analysis in social media research, particularly in identifying temporal rhythms that influence user behavior and content interaction. These insights reinforce existing theories on algorithmic engagement cycles and highlight the importance of quantitative approaches in studying digital trends (Wang et al., 2013; Fanny & Suroyo, 2022).

Practically, the results can help digital marketers determine the optimal posting times, especially during periods of increased user activity, such as weekends. Content creators may also benefit by adjusting their upload schedules to align with these patterns, increasing the visibility and reach of their content. Additionally, TikTok developers could enhance trend prediction features within the platform by incorporating real-time time-series analysis. Overall, this study lays the groundwork for future research that integrates numerical modeling with qualitative factors—such as content type or audience response—to provide a more holistic understanding of content virality on social media platforms (Shen, 2023; Haddock et, 2022). The findings also provide a basis for future research combining numerical data analysis with other factors such as content type or audience reaction.

4. CONCLUSION

From our research, the 3-day moving average analysis results show a fairly cyclical trend in the popularity of the #fyp hashtag on TikTok, demonstrating how the rhythm of user behaviour affects algorithmic engagement patterns. Engagement peaks on weekends, such as the spike of 15.6 billion views on April 19, and declines on weekdays, suggesting behavioural patterns that content creators can leverage to post at strategic times. The findings are also helpful for educators developing digital media literacy curricula and trend analysis, because they reveal how algorithmic patterns and user behaviour influence content visibility and virality on TikTok. By understanding these patterns, educators can design more relevant learning materials that address how trends are formed, spread, and maintained in real-time digital environments. While the moving average method adequately smooths the data and recognizes underlying patterns, it cannot predict sudden viral spikes without it. Future research should include content type classification and audio trend hunting to deepen the understanding of TikTok dynamics. The results of this study provide new knowledge on mathematical models in analysing social media, emphasizing the complex relationship between digital operating systems and human innovation. This research offers actionable insights and strategies in a digital world that will continue to evolve rapidly.

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