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Modelling & Analyzing View Growth Pattern of YouTube Videos inculcating the impact of Subscribers, Word of Mouth and Recommendation Systems

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Abstract
YouTube, one of the prominent online video-sharing platforms, plays a pivotal role in modern media consumption, making it crucial to understand and predict the view-count dynamics of its videos. The viewership of YouTube videos can be influenced by three distinct sources: subscribers, word-of-mouth, and recommendation systems. This paper presents a comprehensive modelling framework that takes into account the view-count obtained through these three sources, assuming that a single view-count can only be attributed to one of these sources at any given time. We investigate the interplay among these sources in shaping YouTube video view-count dynamics, proposing a novel approach to model and analyse their impact on video popularity. Additionally, the VIKOR multi-criteria decision-making method is employed to validate and rank our proposed models. This study's findings deepen our understanding of the intricate mechanisms within the YouTube ecosystem, offering insights for predicting and managing video viewership.

Keywords- Recommendation system, Subscribers, View-count, VIKOR, Word-of-mouth, YouTube.

1. Introduction

YouTube, the most popular video sharing platform and the second most popular social media platform has become an integral part of our daily lives. With over 2.7 billion active users as of 2023, it is a hub for a diverse array of content (Shewale, 2023). The immense popularity of YouTube has forever changed the common man's media consumption habits. Over 122 million users visit YouTube each day to consume 1 billion hours of videos every single day (Shewale, 2023). While serving as a video repository, it also acts as a source of entertainment, news, education and information for a global audience. In the past decade, YouTube has transformed from a platform for sharing amateur videos to a global media powerhouse. The platform hosts content from various categories, providing users with an abundance of options. Furthermore, YouTube has become a vital marketing tool for businesses, celebrities, and influencers, enabling them to reach a vast audience and build a strong online presence.

The role of YouTube in shaping public opinion and influencing societal trends is significant (Burgess and

Green, 2018). The platform has the power to amplify voices, create viral sensations, and drive social change. The ease of accessibility of the platform is empowering individuals to become content producers themselves and to actively participate in shaping public discourse (Jenkins et al., 2015). YouTube's impact on education and learning has also been profound (Greenhow et al., 2009). The platform offers a plethora of educational content, ranging from academic lectures to tutorials and skill-building videos. The visual and interactive nature of YouTube videos has enhanced the learning experience, enabling students to grasp complex concepts more effectively (Burgess and Green, 2018). Moreover, the availability of diverse perspectives and the ability to engage with educators in real-time have fostered a collaborative learning environment (Greenhow et al., 2009).

The growth of YouTube has also been fuelled by advancements in technology and the proliferation of mobile devices. The availability of smartphones and high-speed internet has made video consumption more accessible and convenient. Additionally, the integration of YouTube with other social media platforms has also facilitated content sharing and cross-promotion, further driving user engagement.

From a marketing perspective, social media has become an important channel that strongly aligns with advertising and marketing communications (Zhang and Mao, 2016). Marketers wish to expand their customer base by executing effective promotional campaigns. In recent years, YouTube has emerged as a pivotal marketing platform for brand promotion. Marketers collaborate with YouTube influencers, who have substantial follower bases, to disseminate sponsored content (Acikgoz and Burnaz, 2021). This strategy uses the influencers' reach and credibility to enhance brand visibility and engagement. Consequently, YouTube influencers play a crucial role in shaping consumer perceptions and driving brand loyalty by sharing content that resonates with their followers and aligns with the brand's image and values.

In this context, understanding the factors that drive viewership on YouTube is vital across various fields where the platform plays a significant role. Whether it's in marketing, education, entertainment, or information dissemination, the dynamics of video views are central to the success of content dissemination efforts (Cha et al., 2007). By analysing the factors that influence view-counts, stakeholders in these fields can tailor their content and strategies to maximize reach and engagement, ensuring that their message effectively resonates with their target audience. This connection between content creation and viewership dynamics is crucial for anyone looking to leverage YouTube as a powerful tool in their respective field.

The phenomenon of viewership dynamics on YouTube has been the subject of extensive research over the past decade (Vaish et al., 2012; Pinto et al., 2013; Richier et al., 2014; Bauckhage et al., 2015; Bisht et al., 2019; Aggrawal et al., 2021; Anand et al., 2022), given the platform's significant impact on media consumption patterns and user engagement. The literature in this domain primarily focuses on understanding the factors that influence the view-counts of videos, which is critical for content creators seeking to optimize their reach and engagement on the platform.

1.1 Role of Subscribers in View-count Dynamics
One of the well-established factors influencing the view-count of YouTube videos is the role of subscribers. Subscribers are users who have chosen to follow a particular channel, and they are typically more likely to engage with new content from that channel. They represent a loyal and engaged audience segment on YouTube. Subscribers actively follow channels and receive updates on new content, fostering a consistent viewership base. Understanding how subscriber counts impact video performance and how they interact with other factors is crucial.

Research has shown that channels with a larger subscriber base tend to have higher view-counts for their videos, as subscribers receive notifications about new content and are more likely to view and engage with it (Bärtl, 2018). Moreover, studies have also indicated that the level of engagement from subscribers, including likes, comments, and shares, can further contribute to the visibility of a video, simulating user engagement, thereby influencing its view-count (Yang et al., 2022). Thus, subscribers act as the first step in the ladder of a video's popularity (Maulana et al., 2020).

1.2 Impact of Word-of-Mouth on Video Popularity
Word of mouth, or user-generated buzz, has long been a potent catalyst for video virality. It involves viewers sharing content with their social circles, sparking discussions, and potentially igniting a viral phenomenon (Bi et al., 2019). Analysing the mechanisms through which word of mouth spreads and its correlation with video success is a vital aspect of our proposed framework.

Research has shown that videos that generate high levels of word-of-mouth, as measured by the number of comments, shares, and social media mentions, tend to have higher view-counts (Berger and Milkman, 2012). This phenomenon is often attributed to the social influence of peers and the viral nature of online content, where users are more likely to view and engage with videos that have been recommended or shared by their social networks (Dobele et al., 2007).

1.3 Importance of Recommendation Systems in Content Discovery
YouTube's recommendation algorithms are the secret sauce behind many video success stories. They personalize the user experience by suggesting videos based on viewing history, preferences, and engagement. Unpacking the recommendation system's algorithms, its role in content discovery, and its potential biases are central components of our research (Zhou et al., 2010).

The recommendation system, often overlooked but of paramount importance, wields a considerable influence on the virality and reach of videos on the platform. In essence, it acts as a digital curator, guiding users to content that aligns with their interests and preferences. (Spiliotopoulos et al., 2022) Ensuring that popular videos are not only discovered but also recommended to the right audience is pivotal in expediting the video's journey toward widespread viewership.

While the role of subscribers and word-of-mouth in shaping the view-counts of YouTube videos is well-documented, there is a growing recognition of the importance of recommendation systems in content discovery and user engagement. This system is instrumental in shaping user engagement and content visibility, potentially driving significant portions of a video's view-count. Research has shown that recommendation systems play a crucial role in content discovery on YouTube, with a significant proportion of video views originating from the platform's recommendations (Davidson et al., 2010). Moreover, studies have also highlighted the impact of recommendation systems on user engagement and retention, as users are more likely to spend more time on the platform and view more videos when they are exposed to relevant and personalized recommendations (Zhang et al., 2013).

Table 1 below provides a comparative analysis of the current study with existing literature in the field. It highlights the similarities and differences between the proposed work and previous research, allowing readers to understand the context and the advancements made in this study.

Despite the growing recognition of the importance of recommendation systems in the YouTube ecosystem, there is a dearth of research that specifically models and analyses the impact of recommendation systems as a distinct source of view-count. Most studies have focused on subscribers and word-of-mouth as the primary drivers of video popularity, with limited attention given to the role of recommendation systems.

Table 1. Comparison between proposed and existing work.

Work by Authors → Criteria ↓	Zhou et al. (2010)	Richier et al. (2014)	Bi et al. (2019)	Maulana et al. (2020)	Anand et al. (2021)	Proposed Work
Social Media	✓	✓	✓	✓	✓	✓
View-Count	✓	✓	×	×	×	✓
Subscribers	×	×	×	✓	✓	✓
Word-of-mouth	×	×	✓	×	✓	✓
Recommendation System	✓	×	×	×	×	✓

This study seeks to address this gap by proposing a novel approach to modeling the interplay between subscribers, word-of-mouth, and recommendation systems together in shaping the view-count dynamics of YouTube videos.

The rest of the article has been structured as follows: section 2 discusses the building blocks of the proposed modelling framework followed by the proposed modelling framework in Section 3. Section 4 presents the proposed models and section 5 discusses the model illustration. Discussion and conclusion are presented in Sections 7 and 8 respectively followed by references at the end.

2. Building Block of the Proposed Modelling Framework

2.1 Assumptions

The model proposed in this article is based on the following set of assumptions:

a. The fundamental assumption of the proposed model is that at any specific point in time, only one influence (subscribers, word-of-mouth, or recommendation systems) can affect the view-count dynamics of YouTube videos.
b. The rate of change in view-count varies for each of the three factors.
c. The maximum achievable view-count of a YouTube video is constant.
d. The duration of the YouTube video's popularity is limited.

2.2 Notations

The notations being followed for the proposed modelling framework are as follows:
$\boldsymbol{N}$**:** Total number of potential viewers of a video.
$\boldsymbol{V(t)}$**:** Cumulative number of views by time *'t'*.
$\boldsymbol{V_S}$**:** View count obtained at any given time point *'t'* due to subscribers.
$\boldsymbol{V_{WOM}}$**:** View count obtained at any given time point *'t'* due to word of mouth.
$\boldsymbol{V_{RS}}$**:** View count obtained at any given time point *'t'* due to recommendation system.
$\boldsymbol{b(t)}$**:** Time dependent rate of viewing.
$\boldsymbol{F_i(t)}$**:** Cumulative distribution function, $i = 1,2,3$.
$\boldsymbol{f_i(t)}$**:** Probability density function, $i = 1,2,3$.

3. Proposed Modelling Framework

Aggrawal et al. (2018) introduced a framework that characterized marketing science theory in relation to YouTube's video view counts. Building upon this foundation, Irshad et al. (2019) extended the work by modelling the dynamics of YouTube video popularity. Their model incorporated two key factors: the information spread among netizens, often referred to as word of mouth, and the number of subscribers to a specific video channel. Notably, they provided an alternative formulation for the framework proposed by Aggrawal et al. (2018). This alternative formulation considered a time-dependent rate of viewing, which was instrumental in determining the number of views a video could accumulate given by Equation (1):

$$\frac{dV(t)}{dt} = b(t)[N - V(t)] \tag{1}$$

where, $V(t)$ denotes the cumulative number of views by time 't', N denotes the total number of potential viewers of a video and $b(t)$ is the time dependent rate of viewing. In the present study, a more comprehensive approach is necessary to accommodate the various scenarios prevalent in the market. To achieve this, we employ the hazard rate approach, a widely recognized method in marketing science literature (Bass, 1969; Anand et al., 2016). This approach allows us to utilize the following differential equation to effectively model the process as follows:

$$\frac{dV(t)}{dt} = \frac{f(t)}{1-F(t)}(N - V(t)) \tag{2}$$

where, $F(t)$ is the cumulative distribution function and $f(t)$ is the probability density function.

The above modelling framework can be solved to obtain a closed form solution using the initial condition $V(t = 0) = 0$, to obtain the following equation:

$$V(t) = NF(t) \tag{3}$$

The above equation can also be written as:

$$V(t) = N\int_0^t f(t)\ dt \tag{4}$$

The proposed modelling framework utilises this form to analyse the impact of various identified and defined sources of view count on YouTube videos.

3.1 Viewership via Subscribers, WOM and Recommendation System

In this paper, we examine a scenario where the view-count of a video is influenced by three factors: subscription, word of mouth, and recommendation system. However, at any given point in time, the viewership is attributed solely to one of the aforementioned sources. This implies that if the view-count is being generated by subscribers of the channel where the video is uploaded, the views derived from word-of-mouth and the recommendation system are excluded. A similar approach is employed for the other two sources. Consequently, the framework discussed through Equation no (3) and (4) has been utilized to present a new mathematical representation of this scenario and which can be expressed through the following equation:

$$V(t) = N\int_0^t \left(\left(f_1(t).\overline{F_2(t)}.\overline{F_3(t)}\right) + \left(\overline{F_1(t)}.f_2(t).\overline{F_3(t)}\right) + \left(\overline{F_1(t)}.\overline{F_2(t)}.f_3(t)\right)\right) dt \tag{5}$$

where, $\overline{F(t)} = 1 - F(t)$.

$F_1(t), F_2(t), F_3(t)$ are cumulative distribution functions of view count due to subscription, word of mouth and recommendation system respectively and $f_1(t), f_2(t), f_3(t)$ are the probability density functions.

In the aforesaid Equation (5), the initial segment of the equation, $\left(f_1(t).\overline{F_2(t)}.\overline{F_3(t)}\right)$ pertains to the scenario where the influx of views on an uploaded video is exclusively attributed to the viewing activity of the audience subscribed to the channel. In this case, the views resulting from the other two sources of viewership are not factored in. In a similar way, the subsequent segment of the equation, $\left(\overline{F_1(t)}.f_2(t).\overline{F_3(t)}\right)$ and $\left(\overline{F_1(t)}.\overline{F_2(t)}.f_3(t)\right)$ accounts for the viewership that occurs solely through word of mouth and recommendation system respectively.

The above Equation (5) can also be represented as,

$$V(t) = V_S + V_{WOM} + V_{RS} \tag{6}$$

which means that the view count obtained at any given time point t is due to subscribers (V_S), word of mouth (V_{WOM}) or recommendation system (V_{RS}).

After solving Equation (5), the following equation is obtained:

$$V(t) = N[F_1(t) + F_2(t) + F_3(t) + F_1(t)F_2(t)F_3(t) - F_1(t)F_2(t) - F_2(t)F_3(t) - F_1(t)F_3(t)] \quad (7)$$

The above equation cohesively helps analyse the impact of subscribers, word-of-mouth, and recommendation systems on the view-count dynamics of YouTube videos.

This proposal outlines an extensive modeling framework that seeks to shed light on the intricate dynamics that govern the YouTube ecosystem. In doing so, it aspires to provide a deeper comprehension of how subscription, word of mouth, and the recommendation system collectively shape the consumption and dissemination of content on this influential platform.

4. Proposed Models

***Model* 1:** When the view-count dynamics follows a logistic distribution, characterized by distinct viewing rates b_1, b_2, b_3 and learning parameters $\beta_1, \beta_2, \beta_3$. This indicates that the diffusion of view-count due to subscribers, word-of-mouth, and recommendation system exhibits a logistic growth pattern, starting with a slow rate initially, accelerating rapidly, and eventually slowing down once again.

i.e. $F_i(t) = \frac{1-e^{-b_i t}}{1+\beta_i e^{-b_i t}}$; where, $0 \le b_i \le 1$ and $\beta \ge 1$ (8)

***Model* 2:** When the view-count dynamics conform to a gamma distribution, characterized by diverse rates b_1, b_2, b_3 and shape parameters s_1, s_2, s_3.

i.e. $F_i(t) = (1 - (1 - \Gamma(t, b_i, s_i)))$; where, $b_i \ge 0$ and $s_i \ge 0$ (9)

***Model* 3:** When the view-count dynamics follows an exponential distribution characterized by different rates b_1, b_2, b_3 representing view-count diffusion rates. This suggests that the view-counts due to subscribers, word-of-mouth, and recommendation systems are diffusing within the YouTube platform at a constant rate.

i.e., $F_i(t) = 1 - e^{-b_i t}$; where, $0 \le b_i \le 1$ (10)

***Model* 4:** When the view-count dynamics follows a Weibull distribution characterized by different rates b_1, b_2, b_3 and shape parameters s_1, s_2, s_3. This implies that the rate at which view-counts due to subscribers, feature improvements, and recommendation systems are diffusing within the platform can increase or decrease over time, depending on the shape parameters.

i.e., $F_i(t) = 1 - e^{-b_i (t)^{s_i}}$; where, $0 \le b_i \le 1$ and $s_i \ge 0$ (11)

***Model* 5:** When the view-count dynamics follows a Rayleigh distribution characterized by different rates b_1, b_2, b_3. This suggests that the diffusion of view-counts due to subscribers, word-of-mouth, and recommendation systems in the software is occurring at a linearly increasing rate.

i.e., $F_i(t) = 1 - e^{-b_i (t)^{s_i}}$; where, $0 \le b_i \le 1$ and $s_i = 2$ (12)

***Model* 6:** When the view-count dynamics of YouTube videos follow a normal distribution characterized by mean μ_i and standard deviation σ_i. This implies that the distribution of view-counts due to subscribers, word-of-mouth, and recommendation systems is centred around the mean, and the spread of the distribution is determined by the standard deviation.

i.e., $F_i(t) = (1 - (1 - \psi(t, \mu_i, \sigma_i)))$ (13)

The above equation pertains to the cumulative distribution function (CDF) of a normal distribution governing the view-count. In the context of the normal distribution, the mean serves as the central tendency or average view count, while the standard deviation represents the measure of variability or dispersion around this mean.

The aforementioned models will be validated in the context of our novel proposition of three unique sources of viewership.

5. Model Illustration

The proposed models in this research have been validated using four datasets. The data for this study, shown in Table 2 consists of view-counts of YouTube videos, which were collected at an interval of 4 hours. This time interval was chosen to capture the dynamic and rapidly changing nature of video viewership on the platform. The dataset includes videos across various genres and categories, ensuring a diverse and representative sample for the analysis.

5.1 Model Parameters

In order to evaluate the proposed models, this study has employed the nonlinear least square (NLLS) method (Srinivasan and Mason, 1986) to estimate the unknown parameters. The estimated parameters for each of the four datasets can be found in Tables 3-6.

Table 2. Dataset description.

Dataset	URL	Category	Upload Date	Video Title
DS-I	https://youtu.be/24-YonhNS0Y	Animation and Film	11-07-2023	Painkiller | Official Trailer | Netflix
DS-II	https://youtu.be/S7eJes8AirA	Kids	13-07-2023	Hindi Kids Rhymes
DS-III	https://youtu.be/MmlJb0Pi2-0	Gaming	11-07-2023	Palia - Official Beta Release Trailer
DS-IV	https://youtu.be/97AE_mAlhhc	News and Politics	13-07-2023	Delhi Flood Alert

Table 3. Estimated values of model parameters for DS I.

DS-I						
Parameters	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
N	13047.995	13134.957	13466.202	13294.054	12139.409	12674.441
b_1	0.068	0.001	0.078	0.07	0.001	
b_2	0.039	0.096	0.001	0.002	0.001	
b_3	0.038	0.99	0.001	0.001	0.006	
β_1	1					
β_2	1					
β_3	1					
s_1		2.988		1.053	2	
s_2		1.124		1.053	2	
s_3		41.98		0.395	2	
μ_1						35.417
μ_2						86.486
μ_3						9.29
σ_1						0.931
σ_2						34.663
σ_3						9.214

Table 4. Estimated values of model parameters for DS II.

DS-II						
Parameters	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
N	34849.943	35015.895	38493.894	34875.227	33214.328	33918.355
b_1	0.001	0.236	0.001	0.001	0.001	
b_2	0.001	0.001	0.074	0.001	0.001	
b_3	0.181	0.176	0.001	0.032	0.006	
β_1	7.573					
β_2	51.817					
β_3	2.738					
s_1		10		1.42	2	
s_2		4.159		0.001	2	
s_3		1.809		1.42	2	
μ_1						280.936
μ_2						21748.954
μ_3						8.949
σ_1						39.849
σ_2						8819.124
σ_3						6.343

Table 5. Estimated values of model parameters for DS III.

DS-III						
Parameters	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
N	70983.891	74502.59	72058.811	79839.179	67388.832	73094.242
b_1	0.059	0.883	0.001	0.076	0.001	
b_2	0.059	9.97	0.1	0.133	0.001	
b_3	0.059	0.045	0.001	0.239	0.014	
β_1	1					
β_2	1					
β_3	1					
s_1		39.562		0.144	2	
s_2		500.315		0.68	2	
s_3		0.552		0.027	2	
μ_1						127.132
μ_2						3589.114
μ_3						6.43
σ_1						42.247
σ_2						1234.422
σ_3						15.43

Table 6. Estimated values of model parameters for DS IV.

DS-IV						
Parameters	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
N	13011.457	13211.585	13248.114	15416.541	12128.343	13633.791
b_1	0.067	0.99	0.112	0.035	0.001	
b_2	0.067	0.114	0.001	0.136	0.001	
b_3	0.067	0.003	0.001	0.027	0.028	
β_1	1					
β_2	1					
β_3	1					
s_1		38.159		0.633	2	
s_2		1		0.633	2	
s_3		4.986		0.633	2	
μ_1						62.437
μ_2						52.464
μ_3						11.388
σ_1						90.576
σ_2						1
σ_3						12.972

5.2 Model Validation

The evaluation of different models has been conducted using various comparison metrics, including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), variance, bias, and R-square. The results of the goodness of fit analysis have been presented in Tables 7-10.

Table 7. Values of comparison parameters for DS I.

Models	R^2	Bias	Variance	MAE	RMSE	RMSPE
Model 1	0.994	-7.638	258.029	194.171	258.144	258.014
Model 2	0.996	-15.553	205.764	117.648	206.363	205.726
Model 3	0.996	-30.874	227.892	109.202	230.017	227.824
Model 4	0.996	-21.143	218.574	129.212	219.615	218.525
Model 5	0.913	145.693	1003.746	855.718	1014.482	1003.818
Model 6	0.97	-27.868	598.367	432.658	599.029	598.344

Table 8. Values of comparison parameters for DS II.

Models	R^2	Bias	Variance	MAE	RMSE	RMSPE
Model 1	0.992	-105.16	967.148	659.722	973.002	967.094
Model 2	0.995	-40.327	777.11	557.205	778.184	777.084
Model 3	0.976	-304.88	1609.72	1165.13	1639.1	1609.62
Model 4	0.994	-66.768	848.93	590.625	851.623	848.891
Model 5	0.97	233.331	1807.32	1515.23	1822.72	1807.38
Model 6	0.978	-91.75	1549.44	1194.19	1552.22	1549.41

Table 9. Values of comparison parameters for DS III.

Models	R^2	Bias	Variance	MAE	RMSE	RMSPE
Model 1	0.921	558.537	4155.16	3505.55	4193.16	4155.23
Model 2	0.993	-38.99	1237.77	629.619	1238.4	1237.76
Model 3	0.95	408.966	3333.91	2768.95	3359.32	3333.97
Model 4	0.923	-906.62	4040.27	2470.94	4142.42	4040.15
Model 5	0.73	969.079	7703.56	6491.43	7765.3	7703.62
Model 6	0.949	-246.35	3373.22	2155.27	3382.36	3373.19

Table 10. Values of comparison parameters for DS IV.

Models	R^2	Bias	Variance	MAE	RMSE	RMSPE
Model 1	0.878	84.559	1026.62	801.127	1030.17	1026.66
Model 2	0.91	58.348	884.536	664.592	886.498	884.569
Model 3	0.908	56.005	894.076	681.813	895.865	894.107
Model 4	0.949	-18.795	669.512	443.793	669.781	669.498
Model 5	0.73	78.674	1532.43	1297.25	1534.49	1532.46
Model 6	0.867	-109.81	1070.93	645.475	1076.66	1070.88

The goodness of fit criteria offers valuable insights into model performance by quantitatively assessing how well the proposed models align with observed data. However, it's notable that no single model stands out as the unequivocal best fit among the proposed six models.

5.3 Graphical Analysis

Figures 1-4 represent the accuracy of the proposed models with respect to the original data.

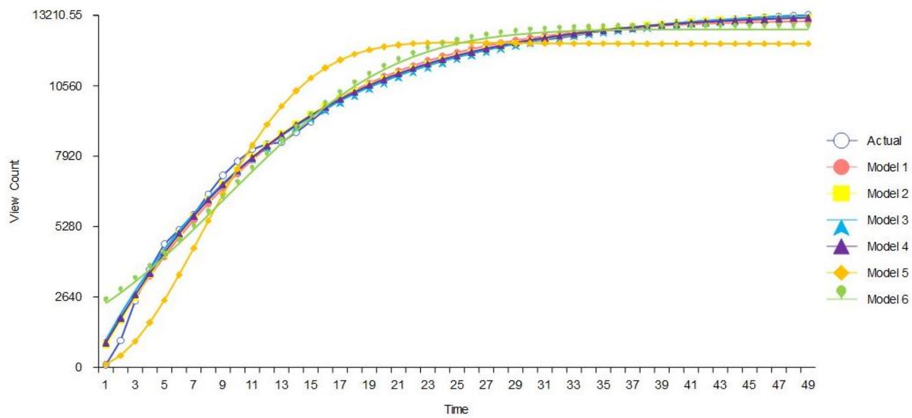

Figure 1. Graphical analysis for DS I.

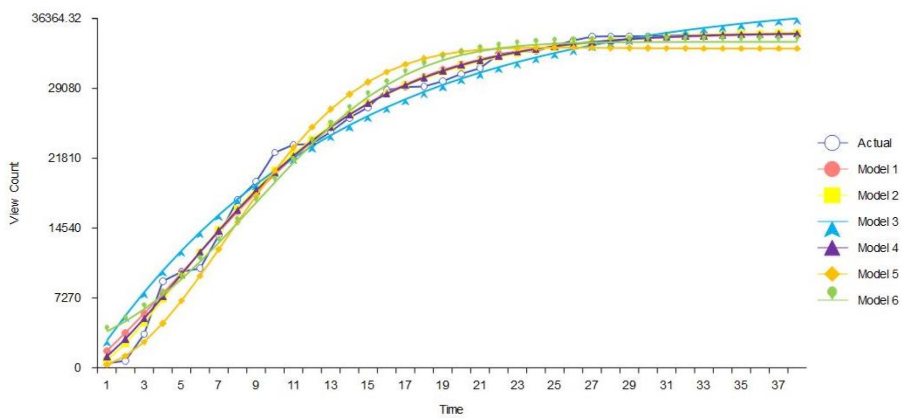

Figure 2. Graphical analysis for DS II.

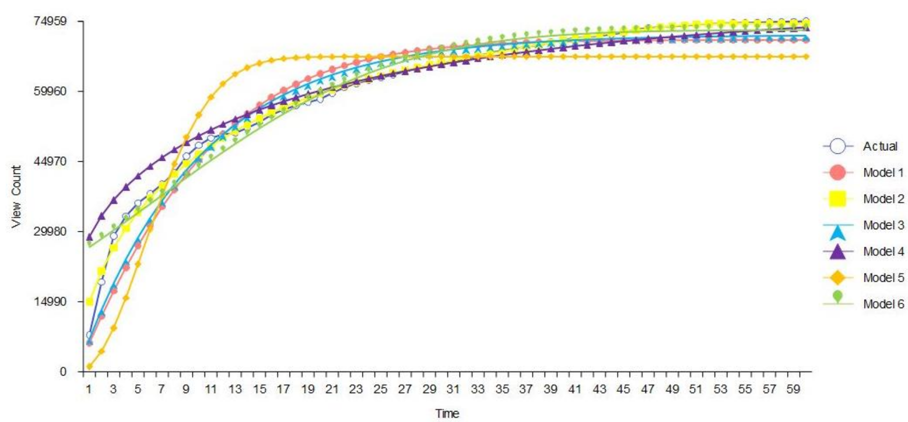

Figure 3. Graphical analysis for DS III.

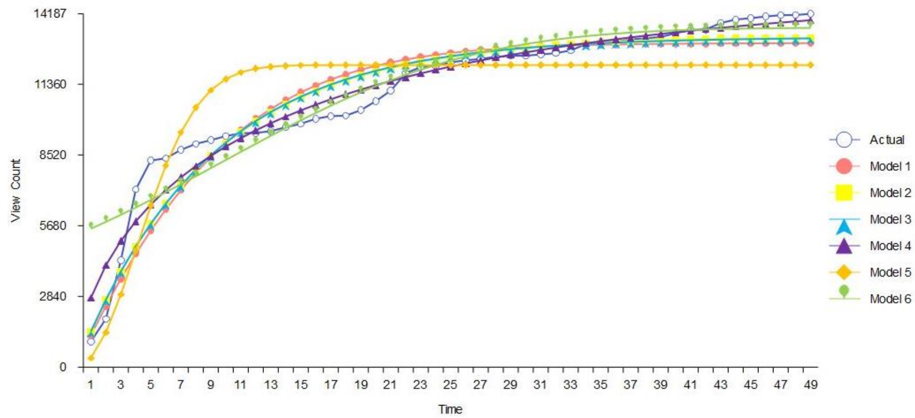

Figure 4. Graphical analysis for DS IV.

The above Figures 1-4 demonstrate that the models exhibit a fairly good fit to the original data, suggesting a favourable alignment between the proposed models and the observed datasets.

6. Ranking the Proposed Models: Utilizing VIKOR

After thorough evaluation of the goodness-of-fit criteria, reaching a definitive conclusion about the best-performing model remains challenging. To address this, a systematic technique for measuring and validating model performances is essential. Therefore, we employ the VIKOR multi-criteria decision-making (MDCM) method on the obtained results. It will offer a comprehensive approach to assess and rank models based on multiple criteria, providing valuable insights into their relative performance and aiding in the selection of the most suitable model for our study.

The VIKOR method, originally developed by Duckstein and Opricovicis (1980) is a MCDM approach that aids in decision-making when confronted with multiple alternatives subject to conflicting and non-commensurable criteria. The essence of VIKOR is to reach a compromised solution, indicative of a resolution attained via mutual concessions. The central aim of this methodology is to pinpoint the most favourable (compromised) solution from the set of available alternatives, with the assurance that it closely approximates the ideal solution (Anand et al., 2022). The steps for using the VIKOR method are as follows:

***Step* 1: Find the best and worst value:** Identify the best (ideal) and worst (anti-ideal) values for each criterion. The best value is the most favourable value for a criterion, while the worst value is the least favourable.

$$X_{ij}{}^{+} = \begin{cases} max \;\; X_{ij}; \text{ for beneficial criteria} \\ min \;\; X_{ij}; \text{ for non-beneficial criteria} \end{cases} \tag{14}$$

$$X_{ij}{}^{-} = \begin{cases} min \;\; X_{ij}; \text{ for beneficial criteria} \\ max \;\; X_{ij}; \text{ for non-beneficial criteria} \end{cases} \tag{15}$$

***Step* 2*:* Calculate the utility and regret measures:** For each alternative, compute the utility measure (S_i) and the regret measure (R_i)based on the normalized decision matrix, best, and worst values.

$$S_i = \sum_{j=1}^{m} \left(w_j \frac{X_i{}^{+} - X_{ij}}{X_i{}^{+} - X_i{}^{-}} \right) \tag{16}$$

$$R_i = \max_j \left(w_j \frac{X_i^{+} - X_{ij}}{X_i^{+} - X_i^{-}} \right) \tag{17}$$

***Step* 3: Determine the VIKOR index:** Calculate the VIKOR index (Q_i) for each alternative by combining the utility and regret measures. The VIKOR index is a weighted sum of S_i and R_i.

$$Q_i = v\left(\frac{S_i - S^*}{S^- - S^*}\right) + (1 - v)\left(\frac{R_i - R^*}{R^- - R^*}\right) \tag{18}$$

where, $S^* = \min_i S_i, S^- = \max_i S_i, R^* = \min_i R_i, R^- = \max_i R_i$.

***Step* 4: Rank the alternatives:** Sort the alternatives based on their VIKOR indices in ascending order. The alternative with the lowest VIKOR index is considered the optimal solution. The outcomes of the VIKOR analysis are presented in Tables 11-14, where the goodness-of-fit values have been employed to assess the alternatives.

Table 11. Ranking of models for DS-I.

Models	Si	Ri	Qi	Rank
Model 1	0.055	0.018	0.052	3
Model 2	0.011	0.009	0	1
Model 3	0.042	0.028	0.074	4
Model 4	0.028	0.016	0.03	2
Model 5	1	0.166	1	6
Model 6	0.393	0.081	0.423	5

Table 12. Ranking of models for DS-II.

Models	Si	Ri	Qi	Rank
Model 1	0.192	0.061	0.06	1
Model 2	0.081	0.081	0.095	3
Model 3	0.639	0.137	0.663	5
Model 4	0.121	0.073	0.078	2
Model 5	1	0.166	1	6
Model 6	0.663	0.124	0.617	4

Table 13. Ranking of models for DS-III.

Models	Si	Ri	Qi	Rank
Model 1	0.483	0.13	0.551	5
Model 2	0.077	0.077	0.085	1
Model 3	0.367	0.116	0.426	4
Model 4	0.315	0.074	0.2	3
Model 5	1	0.166	1	6
Model 6	0.294	0.058	0.117	2

Table 14. Ranking of models for DS-IV.

Models	Si	Ri	Qi	Rank
Model 1	0.503	0.171	0.729	5
Model 2	0.346	0.148	0.52	4
Model 3	0.354	0.146	0.513	3
Model 4	0.08	0.08	0.011	1
Model 5	1	0.166	0.972	6
Model 6	0.335	0.078	0.138	2

Implementing the specified steps, the VIKOR method was systematically applied, and the resultant Tables 11-14 present a clear ranking of the models. Notably, Model II emerged with the highest rank, securing the top position in two datasets. Conversely, Model 5 consistently held the lowest rank across all datasets, indicating a notable contrast in performance among the evaluated models.

7. Discussion

The proposed models have been evaluated and compared using Tables 3-6, which demonstrate a strong correlation between the models. Tables 6-10 depict the performance of these models across four datasets. To further assess the models, the VIKOR multi-criteria decision-making method was employed. The results of the VIKOR analysis are presented in Tables 11-14. The VIKOR results indicate that Model 2 achieved the highest rank, securing the first position for two datasets, while Model 5 consistently ranked the lowest across all datasets. This application of the VIKOR method provides an additional layer of validation for the proposed models, offering valuable insights into their relative performance and rankings.

7.1 Research Contributions

The primary contribution of this study lies in its novel approach to modeling and analysing the impact of subscribers, word-of-mouth, and recommendation systems on the view-count dynamics of YouTube videos. This research advances the existing body of knowledge by providing a more comprehensive and nuanced understanding of the factors influencing video popularity on the platform. This study is among the first to explicitly model the recommendation system as a distinct source of view-count, alongside subscribers and word-of-mouth. By incorporating the recommendation system into the modeling framework, this research addresses a significant gap in the existing literature, which has primarily focused on subscribers and word-of-mouth as the primary drivers of video popularity.

7.2 Implications for Practice

The findings of this study have significant implications for content creators, marketers, and platform managers who aim to optimize their content strategy, audience engagement, and promotional efforts on YouTube.

a. Content Strategy and Audience Engagement

The study highlights the importance of subscribers, word-of-mouth, and recommendation systems as key drivers of video popularity on YouTube. Content creators should consider these factors when developing their content strategy and audience engagement practices. For example, fostering a loyal subscriber base and encouraging viewers to share and comment on videos can enhance word-of-mouth and contribute to higher view-counts.

b. Leveraging Recommendation Systems

The study underscores the significant impact of recommendation systems on video viewership. Content creators and marketers should aim to understand the factors that influence the recommendation algorithm, such as user engagement metrics (e.g., like-to-dislike ratio, click-through rate). By optimizing these metrics, creators can improve the visibility of their videos and increase the likelihood of being recommended to potential viewers.

c. Data-Driven Decision Making

The research findings highlight the importance of data-driven decision making in optimizing video viewership on YouTube. Platform managers and marketers should leverage analytics and data insights to monitor the performance of videos, assess the impact of subscribers, word-of-mouth, and recommendation systems, and make informed decisions about content promotion and distribution. By analysing data on subscriber engagement, social media shares, and recommendation system metrics, platform managers can identify trends and patterns in viewer behaviour. This information can inform the development of targeted marketing campaigns, content curation strategies, and user retention efforts.

d. Audience Interaction and Community Building

The study emphasizes the role of word-of-mouth in driving video viewership. Content creators should actively engage with their audience through comments, social media interactions, and community-building initiatives. By fostering a sense of community and encouraging viewers to share their thoughts and experiences, creators can enhance word-of-mouth and increase the organic reach of their videos.

8. Conclusion

As YouTube continues to evolve and maintain its pivotal role in modern media consumption, the imperative to understand the intricate dynamics of video viewership remains a critical area of research. This study uncovers the nuanced interplay between subscribers, word-of-mouth, and recommendation systems which are the integral factors in shaping YouTube video view-count dynamics. A noteworthy contribution of the current work is the explicit modeling of the recommendation system as a distinct view-count source alongside subscribers and word-of-mouth which enriches existing models, offering a more comprehensive perspective. Moreover, the study employs the VIKOR multi-criteria decision-making method to validate and compare the proposed models, enhancing the robustness of the research findings. The implications of this study extend significantly to content creators, marketers, and platform administrators, offering valuable insights into optimizing video viewership strategies. In conclusion, this study marks a critical step in better understanding of the intricate dynamics of YouTube video viewership.

8.1 Limitations

The present study does not consider the potential effects of external factors or alterations to the platform's algorithms, both of which can significantly influence video viewership. Consequently, future research could enhance the robustness of the findings by addressing these aspects.

8.2 Future Research Directions

Future research could conduct a longitudinal analysis of view-count dynamics, examining the trends and fluctuations in video viewership over extended periods. This could provide insights into the sustained impact of subscribers, word-of-mouth, and recommendation systems on video popularity.

Additionally, a comparative analysis of view-count dynamics across different video-sharing platforms (e.g., Vimeo, Dailymotion) could provide a broader understanding of the factors influencing video popularity. This could help identify platform-specific dynamics and inform content creators and marketers about the unique characteristics of each platform.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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