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# An analysis of YouTube as a knowledge-sharing platform for mango cultivation

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## Abstract

This research delved into the dynamics of knowledge-sharing on YouTube within the context of mango cultivation. Analyzing a diverse dataset of 153 videos, the impact of video originality, channel categories, and geographical locations on viewership and subscriber counts was investigated. While descriptive statistics suggested that, on average, original videos received more views, an ANOVA revealed a non-significant difference in viewership between original and non-original videos, indicating additional factors at play. Geographical locations demonstrated significant variations in subscriber counts, emphasizing the influence of location on mean views. Correlation analysis underscored strong positive associations between subscriber counts and views/likes, highlighting the key role of subscribers in measuring audience engagement. Utilizing Principal Components Analysis (PCA), we identified six components explaining 100% of the dataset variance. Component 1 represented overall video popularity, while Component 2 captured nuances of content quality and appreciation. In conclusion, this study offers valuable insights for content creators and researchers navigating YouTube's landscape for knowledge-sharing in mango cultivation. While originality and channel categories may not be the primary drivers of viewership, geographical location and subscriber counts emerged as crucial influencers. The PCA and correlation analyses reveal intricate aspects that contribute to video performance, enabling stakeholders to enhance content strategies for efficient knowledge dissemination on YouTube.

**Key words:** YouTube, mango cultivation, video originality, channel categories, geographical location, subscriber counts, principal components analysis, correlation analysis.

## Introduction

The dissemination of agricultural knowledge is a dynamic field, and YouTube has developed into a powerful and easily accessible platform that transcends geographical boundaries (Sinha *et al.*, 2020). Social learning, which is a collaborative process that involves a wide variety of stakeholders, is essential for the purpose of assisting farmers in communicating, reflecting, and gaining a shared understanding of issues that are common to the industry (Hegde *et al.*, 2017).

*Mango cultivation*, an integral component of global agriculture, presents a rich tapestry of practices and regional nuances (Rajan, 2021). As traditional agricultural practices integrate with digital platforms, understanding the dynamics of information dissemination on YouTube becomes pivotal for stakeholders in the mango cultivation domain also. This research aims to uncover the factors influencing the viewership and engagement of mango cultivation-related content on YouTube.

In the investigation of the National Mango Database, an intriguing pattern emerged among mango enthusiasts (Rajan *et al.*, 2020). Just as individuals selectively explored different modules on the database to satiate their curiosity about mango-related information, YouTube viewers might follow a differnt pattern. Whether navigating diverse varieties, exploring cultivation technology, or delving into videos on YouTube, mango enthusiasts demonstrated a preference for content tailored to their specific interests. Recognizing this parallel, it becomes crucial to acknowledge the diverse preferences within the mango community, a phenomenon that may extend to the patterns followed by YouTube viewers. This understanding underscores the importance of accommodating varied interests through analysis of dynamic video content on platforms like YouTube.

Scholars have extensively utilized internet video sharing for two primary objectives. Firstly, it serves as a platform for informal scholarly communication. Secondly, it acts as an engagement tool in contemporary society. This technology has also found application in the realm of mango cultivation, functioning as both a promotional tool for disseminating information about technology and a medium for public engagement with mango related technologies. Role of YouTube, the leading internet video sharing platform with publicly accessible content, in knowledge sharing across diverse fields. The focus then shifts to exploring how YouTube portrays information related to mango cultivation.

The significance of YouTube in relation to agriculture is something that simply cannot be overstated. As a medium that is both visual and interactive, YouTube provides a dynamic platform that allows farmers, agricultural enthusiasts, and researchers to share, access, and exchange information (Chivers *et al.*, 2023). When it comes to conveying complex agricultural practices, pest control methods, and innovative techniques in mango cultivation, video content offers a method that is both visually appealing and practical. YouTube’s accessibility ensures that this information is disseminated to a wide range of people all over the world, which contributes to the democratization of agricultural information (Singh *et al.*, 2023). Among the top one hundred most-viewed videos on YouTube, there is a dearth of comprehensive and methodical measurement studies that aim to uncover the characteristics of videos that address mango cultivation issues. These studies are a lack of comprehensive and methodical measurement studies. Information regarding the existing gap that is associated with this particular subject matter is something that should be gathered as soon as possible.

The objective of this study was to contribute to the expanding body of knowledge on effective knowledge-sharing strategies on YouTube and emphasize the significance of considering multifaceted factors within the mango cultivation domain. The amalgamation of statistical analyses, geographical considerations, and content dynamics aimed to pave the way for a more informed and targeted approach to knowledge dissemination on YouTube, with the goal of ensuring that mango cultivation practices reached and benefited a global audience.

## Material and methods

**Data collection:** YouTube, a widely-used video sharing platform, was the primary source of data. The platform offers a vast array of video content on various subjects, including mango cultivation.

**Search criteria**: Keywords mango cultivation, mango farming techniques, mango plantation, mango nursery, good horticultural practices, crop production techniques, crop protection measures, harvesting methods, market connections and related phrases were used. Videos uploaded between July 2021 and August 2023 were studied.

**Data cleaning**: Preliminary data cleaning was performed to remove duplicates, filter out videos with unrelated content, which may have been captured due to broad search criteria and standardize date formats.

**Database creation**: A structured database was designed to store the extracted data, including the following variable for each video. Video Title; Channel Name; Subscribers; Upload Date; Views; Likes; Video Originality (Y=Yes, N=No); Geographical Location; Rating by Media Person (0-10); Rating by Farmers (0-10); Tags used by uploader; Channel Category (M= Media Channel, G=Government Channel, *P*=Private You tuber. The methodology employed for the comprehensive analysis of YouTube video performance encompassed various statistical techniques and data processing steps. In the investigation of video originality, a dataset containing 153 videos categorized as non-original (N) or original (Y) was utilized.

**Statistical analysis:** Correlation analysis delved into the relationships between six variables, including Subscribers, Number of days after upload, Views, Likes, Rating by Media Person (0-10), and Rating by Farmers (0-10). For an understanding of video content dynamics, a Principal Components Analysis (PCA) was conducted on a dataset featuring above mentioned six variables. including Subscribers, Data standardization preceded PCA, enabling the identification of key components explaining variance and the assessment of weights of original variables on these components. The exploration of subscribers across different channel categories involved ANOVA analysis, uncovering significant differences in mean subscriber counts. Geographical location's impact on mean views was assessed through descriptive statistics and ANOVA analysis. The breakdown of views across diverse locations offered valuable insights into the role of geography in influencing video performance. All data analyses were conducted using SPSS V. 15.

## Results and discussion

In this research investigation, a study was conducted to compare the viewership of videos based on their originality, categorized as either non-original (N) or original (Y). Descriptive statistics revealed that among the 153 videos analyzed, 26 were non-original with an average of 207,911 views, while 127 were original with an average of 325,163 views. The overall average views for all videos stood at 305,237. The analysis extended to an ANOVA table, where the F-Ratio was found to be 0.37 with an associated *P*-value of 0.5455. The non-significant P-Value suggests that there is no statistically significant difference in viewership between non-original and original videos. The sum of squares within and between groups contributed to the overall sum of squares, emphasizing the distribution of views. Therefore, this study concludes that, based on the provided data, there is no discernible impact of video originality on the number of views, indicating that other factors may contribute to viewership variations. These findings are pertinent for researchers and content creators seeking insights into the factors influencing video popularity and audience engagement (Table 1).

Table 1. Effect of video originality on number of views

| Video originality | Count | Average |
|---|---|---|
| No | 26 | 207911 |
| Yes | 127 | 325163 |
| Total | 153 | 305237 |
| F-Ratio | 0.37 | |
| P-Value | 0.54 | |

**Correlation studies**: The correlation analysis reveals several meaningful associations among the key variables related to video content. The positive correlation between subscribers and both views (r = 0.102) and Likes (r = 0.214) suggests that a higher number of subscribers are associated with increased viewership and appreciation in the form of likes. Additionally, the strong positive correlation between Views and Likes (r = 0.840) indicates that videos with higher views tend to accumulate more likes, highlighting a close relationship between these two metrics.

On the other hand, no significant correlations were found between Subscribers and the duration of video availability (No of days) or the ratings provided by media persons. This suggests that subscriber count may not be strongly influenced by the duration a video has been available or the ratings assigned by media professionals.

An interesting observation is the substantial positive correlation (r = 0.74) between the ratings assigned by media persons and farmers. this suggests a degree of agreement or alignment in the perceptions of media professionals and the farming community regarding the videos (Table 2).

Overall, these correlation results provide valuable insights into the dynamics of video performance, offering potential avenues for content creators and researchers to focus on aspects that correlate strongly with subscriber counts and engagement metrics.

Table 2. Correlation of number of subscribers with other variables

| Variable | Subscribers | No of days after upload | Views | Likes | Rating by media Person | Rating by farmers |
|---|---|---|---|---|---|---|
| Subscribers | 1.000 | 0.044 | 0.102 | 0.214 | 0.057 | 0.059 |
| No of days after upload | 0.044 | 1.000 | 0.224 | 0.339 | -0.107 | -0.208 |
| Views | 0.102 | 0.224 | 1.000 | 0.840 | 0.056 | 0.012 |
| Likes | 0.214 | 0.339 | 0.840 | 1.000 | 0.135 | 0.067 |
| Rating by media Person | 0.057 | -0.107 | 0.056 | 0.135 | 1.000 | 0.740 |
| Rating by farmers | 0.059 | -0.208 | 0.012 | 0.067 | 0.740 | 1.000 |

The analysis of subscribers across channel categories (G, M, P) yields meaningful insights into the factors influencing subscriber counts in the dataset. The summary statistics indicate a substantial variation in average subscriber counts, with videos categorized under M (media channel) exhibiting a significantly higher average (3,518,080 subscribers) compared to government (433,012 subscribers) and private channel (349,697 subscribers).

The ANOVA results confirm the observed differences, revealing a significant main effect of channel category on subscriber counts (F-Ratio = 11.08, p-value = 0.0001). This indicates that the choice of channel category significantly impacts the number of subscribers a video attracts. The LSD intervals provide context by illustrating the range of subscriber counts within each category (Table 3)

These findings suggest that content creators should pay careful attention to the selection of channel categories, particularly favoring the Media Chann category for potentially higher subscriber engagement. Understanding these patterns allows for more informed content strategies and targeted promotional efforts, ultimately optimizing subscriber counts and enhancing the overall impact of video content.

Table 3. Effect channel categories of subscribers

| Level | Count | Mean | *F*-Ratio | *P* Value |
|---|---|---|---|---|
| Government | 1 | 433012.0 | 11.08 | 0.0001 |
| Media channel | 11 | 3518080.0 | | |
| Private channel | 141 | 349697.0 | | |
| Total | 153 | 578033.0 | | |

**Geographical location and views**: The breakdown table of descriptive statistics for Views across different geographical locations provides a comprehensive overview of the data. The table includes mean views, the number of observations (N), and the standard deviation for each geographical location. Notably, the "All Groups" row summarizes the total views for all 153 observations. The subsequent analysis of variance (ANOVA) further examines the impact of geographical location on views. The significant F-statistic (F = 2.07, $P$ = 0.002) indicates that there are statistically significant differences in mean views across the various geographical locations (Table 4). The significant effect suggests that the observed variations in mean views are not merely due to random chance but are associated with the geographical location. This information is crucial for content creators and researchers, as it indicates that the choice of geographical location plays a significant role in influencing the number of views a video receives.

Table 4. Effect of geographical location on the views

| Geographical Location | Means | N | SD |
|---|---|---|---|
| Kolkata, West Bengal | 99962 | 6 | 178542 |
| UD | 232009 | 68 | 414866 |
| Lucknow | 348856 | 30 | 1458559 |
| Sitapur, UP | 8461 | 2 | 3502 |
| Haryana | 45829 | 2 | 49115 |
| Sirohi, rajasthan | 4768 | 1 | 0 |
| Anand, Gujrat | 111343 | 1 | 0 |
| Basti, UP | 20402 | 3 | 21035 |
| Bhopal, MP | 783 | 1 | 0 |
| Alwar, Rajasthan | 9769 | 1 | 0 |
| Chattisgarh | 9465 | 1 | 0 |
| Nimeda, Rajasthan | 4923 | 1 | 0 |
| Ashok Nagar | 6931 | 1 | 0 |
| Bhagalpur, Bihar | 46284 | 1 | 0 |
| Jharkhand | 143651 | 1 | 0 |
| Jashpur Nagar Chattishgarh | 6026 | 2 | 1847 |
| West Bengal | 116325 | 4 | 104052 |
| Raipur, Chattisgarh | 4947 | 1 | 0 |
| Malda | 12172 | 1 | 0 |
| Nalanda, Bihar | 1293 | 1 | 0 |
| Bihar | 609234 | 4 | 465096 |
| Assam | 3463281 | 2 | 656675 |
| Maharashtra | 514210 | 4 | 953562 |
| Basti | 71671 | 2 | 15863 |
| Vadodara, Gujrat | 113507 | 1 | 0 |
| MP | 4896807 | 1 | 0 |
| Delhi | 380616 | 2 | 477924 |
| Kachch, Gujrat | 11937 | 1 | 0 |
| Gorakhpur, UP | 9850 | 1 | 0 |
| Uttar Pradesh | 4390 | 1 | 0 |
| Rajasthan | 151584 | 1 | 0 |
| Ambala, Haryana | 688931 | 1 | 0 |
| Sitamani, Bihar | 45741 | 1 | 0 |
| Gujrat | 304060 | 2 | 377604 |
| All Groups | 305237 | 153 | 897070 |
| | *F*= 2.078 | *P*=0.002 | |

UD=Undisclosed

**Principal Components Analysis (PCA):** The analysis was conducted on a dataset comprising six variables related to video content: Subscribers, Number of Days, Views, Likes, Rating by Media Person (on a scale of 0-10), and Rating by Farmers (on a scale of 0-10). The analysis included 153 complete cases, with missing values treated through listwise deletion, and the data were standardized. The PCA resulted in the extraction of six principal components, each contributing to the overall variance in the dataset. The eigenvalues and percentages of variance explained by each component are as follows: Component 1 (2.065, 34.431%), Component 2 (1.803, 30.053%), Component 3 (0.952, 15.870%), Component 4 (0.788, 13.143%), Component 5 (0.252, 4.206%), and Component 6 (0.137, 2.297%). These components collectively explain 100% of the variance in the data. The weights of each original variable on the extracted components provide insights into the contribution of each variable to the identified components. For instance, Subscribers has a significant positive weight on Component 3, suggesting a strong influence on this component. Similarly, Likes has a notable positive weight on Component 5, while Rating by Media Person and Rating by Farmers contribute substantially to Component

2. These results offer a reduced-dimensional representation of the data, highlighting the underlying structure and relationships among the original variables (Table 5).

Content creators and researchers can utilize this information to understand the key factors contributing to video performance and tailor their strategies accordingly. The Principal Components Analysis (PCA) yielded two key components, each shedding light on distinct dimensions influencing video performance. Component 1 accounts for 34.431% of the variance and showcases a comprehensive measure of video popularity. Positive weights are observed across all variables, emphasizing the importance of high subscriber counts, increased duration of video availability, elevated views, likes, and positive ratings from both Media Persons and Farmers. Component 1 appears to encapsulate a holistic metric indicative of a video's widespread appeal and audience engagement.

On the other hand, Component 2, explaining 30.053% of the variance, highlights a nuanced interplay between content quality, audience appreciation, and the temporal aspect of video availability. Positive weights on ratings by Media Persons and Farmers suggest that higher ratings strongly contribute to this component. Notably, the negative weight on the duration of video availability suggests that Component 2 may represent a measure of content quality and appreciation relative to the duration a video has been available (Table 6). In essence, these components offer valuable insights for content creators and researchers, providing a balanced understanding of the multifaceted factors influencing video performance. By considering the nuanced aspects of popularity, audience engagement, content quality, and temporal dynamics, stakeholders can refine their strategies to optimize video content and enhance its impact on diverse audiences.

Table 5. Eigenvalue and variance explained

| Component Number | Eigenvalue | Percent of variance | Cumulative percentage |
|---|---|---|---|
| 1 | 2.07 | 34.43 | 34.43 |
| 2 | 1.80 | 30.05 | 64.48 |
| 3 | 0.95 | 15.87 | 80.35 |
| 4 | 0.79 | 13.14 | 93.50 |
| 5 | 0.25 | 4.21 | 97.70 |
| 6 | 0.14 | 2.30 | 100.00 |

A biplot analysis was performed on a dataset with six video content variables, including Subscribers, number of days after upload, Views, Likes, Rating by Media Person, and Rating by Farmers. Subscribers, Views, Likes, and Ratings (both Media Persons and Farmers) exhibited positive associations, as indicated by aligned vectors, suggesting that high subscriber counts correlated with increased views, likes, and positive ratings (Fig. 1). The biplot enabled content creators to discern the most influential variables in shaping video success, aiding in the tailoring of strategies based on identified patterns.

The key popularity metrics of online videos, particularly focusing on the number of views, user likes and dislikes, and the number of comments. The findings align with existing literature (Kong *et al.*, 2018; Xu *et al.*, 2016), emphasizing the prevalence of views as a primary indicator of video popularity. The study corroborates the notion that popular videos not only accumulate high view counts but also receive increased user engagement in the form of comments, ratings, and likes (Chatzopoulou *et al.*, 2010).

Table 6. Weights of 6 principal component

| Variable | Component | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Subscribers | 0.22 | 0.04 | 0.97 | 0.07 | -0.01 | 0.09 |
| No of days after upload | 0.30 | -0.32 | -0.13 | 0.87 | 0.10 | 0.12 |
| Views | 0.61 | -0.11 | -0.17 | -0.38 | 0.03 | 0.66 |
| Likes | 0.66 | -0.08 | -0.06 | -0.16 | -0.02 | -0.73 |
| Rating by Media Person | 0.19 | 0.65 | -0.10 | 0.23 | -0.69 | 0.07 |

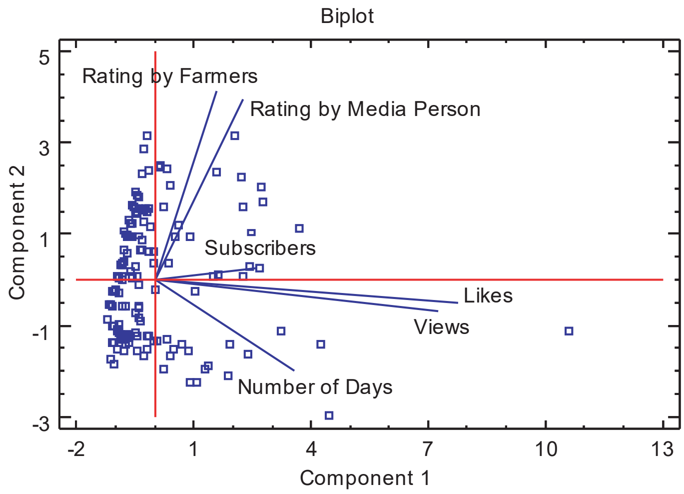


Fig.1. PCA biplot showing PCA scores and loading of variables (vectors).

This underscores the interconnected nature of these popularity metrics, indicating that high engagement often accompanies high viewership.

One notable challenge discussed in the literature is the temporal aspect of video popularity. The observation that online videos experience a surge in daily views upon initial posting introduces a grey area in comparing videos of different ages. The study acknowledges the difficulty in establishing a fair comparison between a recently posted video with a substantial view count and an older video with an equally impressive total view count. While the concern is valid, the lack of a universally agreed-upon formula for such comparisons poses a significant challenge. However, the study suggests that a fairer approach is to compare the total view counts of videos with similar ages. This recommendation reflects a pragmatic stance, acknowledging the inherent dynamics of online video popularity and the challenges associated with comparing videos across different time spans.

In practical terms, content creators and researchers should consider the temporal dynamics of video popularity when interpreting and comparing metrics. Recognizing the initial surge in daily views for recently posted videos can provide insights into the immediate impact of content. Additionally, the study's emphasis on comparing videos of similar ages aligns with a more equitable evaluation, considering the varying trajectories of popularity over time.

In conclusion, this study contributes valuable insights into the interconnected nature of popularity metrics for online videos and addresses the nuanced challenge of comparing videos of different ages. The findings underscore the importance of considering both views and engagement metrics in comprehensively evaluating video popularity. However, further research may be warranted to develop standardized approaches for comparing videos across diverse temporal contexts, providing a more robust framework for understanding the evolving dynamics of online video popularity.

## References

Chatzopoulou, G., C. Sheng and M. Faloutsos, *2010. A first step towards* understanding popularity on YouTube, In: Proceedings of the *IEEE Conf. Comput. Commun. INFOCOM*, 2010.

Chivers, C.A., K. Bliss, A. de Boon, L. Lishman, J. Schillings, R. Smith and D.C. Rose, 2023. Videos and podcasts for delivering agricultural exte.sion: Achieving credibility, relevance, legitimacy and accessibility. *J. Agric. Educ. Extens.*, 29(2), pp.173-197.

Hegde, N., M. Elias, H.A.H. Lamers and M. Hegde, 2017. Engaging local communities in social learning for inclusive management of native fruit trees in the Central Western Ghats, India. *For. Trees Livelihoods*, 26(1):.65-83.

Kong, Q., M.A. Rizoiu, S.Wu and L. Xie, 2018. Will This Video Go Viral: Explaining and Predicting the Popularity of YouTube Videos, in Companion Proceedings of The Web Conference, April, 2018, pp.175-178.

Rajan, S. 2021. *Mango: The King of Fruits. The Mango Genome*, *CPG*, Chittaranjan Kole (Ed), Springer Nature, pp.1-12.

Rajan, S., P.K. Mishra, V. Srivastav, K. Aditya, P. Sagar and P.K. Tripathi, 2020. A study on the visitor preference for different modules of the National Mango Database. *J. Appl. Hortic.*, 22(2): 117-121.

Singh, N.K., N.H. Sunitha, G. Tripathi, D.R.K. Saikanth, A. Sharma, A.E. Jose and M.V. Mary, 2023. Impact of digital technologies in agricultural extension. *Asian J. Agric. Extens. Econ. Sociol.*, 41(9): pp.963-970.

Sinha, A. and S. Biswas, 2023. ICT and social media application in the development of agricultural extension organization. In: *Innov. Extens. Approaches Sustain. Dev. Extens. Organ.* [E-book] Hyderabad: WB University of Animal & Fishery Sciences, Kolkata & National Institute of Agricultural Extension Management, Hyderabad, India, p76.

Xu, W.W., J.Y. Park, J.Y. Kim and H.W. Park, 2016. Networked cultural diffusion and creation on YouTube: An analysis of YouTube memes, *J. Broadcast. Electron. Media*, 60(1): 104el22.

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