Quantifying the Dominant Role of Channel Audience in Predicting YouTube Success with Machine Learning

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ABSTRACT

This study investigates the determinants of YouTube video virality by quantifying the relative influence of audience capital and metadata optimization using machine-learning techniques. Employing a quantitative, cross-sectional design, metadata from the top 100 YouTube music videos of 2025 was analyzed to predict video popularity, measured by view count. After data preprocessing and feature engineering, two supervised regression models — Multiple Linear Regression and Random Forest Regressor — were trained and evaluated. The linear model performed poorly ($R^2 = -0.0680$; RMSE = 1.0970), indicating that linear assumptions failed to capture the complex relationships among features. In contrast, the Random Forest model achieved strong predictive performance ($R^2 = 0.7157$; RMSE = 0.5660; OOB = 0.7051) and provided interpretable feature-importance metrics. Results revealed that channel_follower_count overwhelmingly dominated all other predictors, accounting for over 80% of the total importance score, while metadata-related variables such as description_length, tag_count, and categories contributed marginally. These findings empirically support the thesis that a creator's accumulated audience capital is the primary determinant of virality, reflecting the self-reinforcing dynamics of the digital attention economy. The study highlights the limitations of content-level optimization strategies and underscores the structural advantages enjoyed by established creators in algorithmic ecosystems. Implications extend to platform governance, creator strategy, and digital inequality, emphasizing the need for more transparent and equitable recommendation systems.

Keywords YouTube virality; machine learning; platform capital; algorithmic visibility; audience engagement

Submitted 30 September 2025
Accepted 24 October 2025
Published 1 December 2025

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Introduction

The digital era has ushered in an "attention economy," in which user attention operates as a scarce and highly valuable resource [1]. Rather than competing for material goods or broadcast airtime, platforms now compete for moments of user engagement—clicks, views, and shares—that can be directly monetized through advertising and algorithmic amplification. Within this environment, cultural visibility and economic power converge: whoever captures attention gains both symbolic and financial capital. Nowhere is this more evident than in the online music ecosystem, where attention determines not only popularity but also the very survival of artists and their creative labor.

YouTube has become the central node in this attention-driven infrastructure. Once merely a repository for amateur videos, it has evolved into a dominant platform for global music discovery, effectively supplanting traditional channels such as radio, television, and MTV [2], [3]. Its hybrid nature—simultaneously a search engine, social network, and streaming service—allows artists to reach audiences directly while users curate their own listening experiences. This shift

How to cite this article: N.C.Ramadani and S.Fahreza, "Quantifying the Dominant Role of Channel Audience in Predicting YouTube Success with Machine Learning ," *J. Digit. Soc.*, vol. 1, no. 4, pp. 258-271, 2025.

has redefined the relationship between creator and consumer, turning view counts, likes, and comments into public markers of legitimacy and influence [4].

In this socio-technical configuration, the YouTube "view count" functions as far more than a vanity metric. It serves as a proxy for both cultural resonance and economic performance, shaping record-label decisions, recommendation algorithms, and even award nominations [5]. A single viral spike can transform an obscure musician into a global phenomenon overnight. Consequently, attention itself becomes quantifiable—tracked, optimized, and translated into advertising revenue or sponsorship deals. Understanding what drives these numbers is thus not only an analytical challenge but also a critical cultural inquiry into how value is produced in digital society.

Despite its pervasiveness, the concept of "virality" remains enigmatic. Every minute, thousands of new music videos are uploaded, yet only a tiny fraction attain massive visibility or cultural staying power. Common explanations—such as "a good song goes viral"—fail to capture the systemic complexity underlying these outcomes. Prior research identifies three intertwined domains shaping virality: audience influence, content characteristics, and platform mechanics [6], [7]. Together they form what might be termed the anatomy of virality—a structure that demands quantitative dissection rather than anecdotal speculation.

Two forces dominate this anatomy. The first is audience influence: creators with substantial subscriber bases enjoy an initial boost in visibility because their uploads are immediately disseminated to established followers, producing rapid early engagement that feeds algorithmic recommendation loops [8], [9]. The second is optimization effort: the deliberate crafting of metadata—titles, tags, and descriptions—to make content legible to the algorithm and easily discoverable by users. In practice, creators constantly balance these forces, leveraging audience capital while tailoring videos to algorithmic preferences, yet the relative strength of each remains unclear.

While numerous qualitative studies examine virality, most focus on descriptive patterns or ethnographic accounts rather than rigorous quantification [10]. Research often treats follower count and metadata optimization as parallel predictors without measuring their comparative impact on view counts. This absence of quantification represents a critical limitation: knowing that both matter is insufficient if we cannot specify which exerts greater predictive power. Moreover, prior works rarely apply advanced machine-learning methods capable of modeling non-linear interactions among these variables [11]. As a result, our understanding of digital success remains partial and theoretically imbalanced.

Addressing this gap requires moving beyond correlation toward prediction. By leveraging machine-learning models—particularly ensemble algorithms such as Random Forest or XGBoost—it becomes possible to rank features by importance and estimate how much each contributes to overall success. Quantitative modeling allows scholars to empirically evaluate whether platform capital (i.e., audience size) outweighs optimization effort (metadata quality) in determining a video's performance. Such an approach aligns with recent calls in platform-studies research to integrate computational social science with critical theory, yielding reproducible insights into algorithmic culture.

This study therefore argues that the anatomy of virality on YouTube is dominated by a creator's pre-existing audience size—a form of accumulated platform capital whose predictive power significantly surpasses that of content-specific metadata optimization. To substantiate this claim, three objectives guide the research: (1) to construct a machine-learning model capable of predicting a music video's view count from its publicly available metadata; (2) to demonstrate the limitations of linear regression models in capturing non-linear relationships between predictors and outcomes; and (3) to quantify and rank the relative importance of audience-related and optimization-related features using model-derived importance metrics. By systematically comparing these dimensions, the study contributes both to computational understandings of digital virality and to broader debates on inequality and visibility within the platformized music economy.

Literature Review

YouTube as a Governed Sociotechnical System

YouTube functions not merely as a content-hosting website but as a governed sociotechnical system in which human behavior and algorithmic processes are mutually constitutive. Within such systems, the technical architecture—recommendation engines, ranking algorithms, and interface design—actively shapes cultural production and user engagement [12]. Rather than acting as neutral intermediaries, platforms operate as regulators of visibility, curating which voices are amplified and which remain obscure. This aligns with notion of platform governance, which highlights how algorithms embed platform interests—commercial, cultural, and political—into seemingly objective technical processes.

Algorithmic governance on YouTube thus reflects both economic imperatives and sociocultural biases. As [13] observes, recommendation systems are tuned to maximize watch time and click-through rates, effectively rewarding content that sustains engagement regardless of its artistic or informational quality. Research [14] further argue that this engagement-driven optimization often leads to a “feedback spiral,” wherein the same categories of content repeatedly dominate visibility metrics. In this way, YouTube's algorithmic design implicitly defines what counts as successful content within the digital attention economy.

Empirical studies illustrate that this governance structure can have wide-ranging effects on public discourse. Research [15] demonstrated that during the COVID-19 pandemic, YouTube's recommendation engine clustered videos around specific narrative themes—such as vaccination or conspiracy—thereby steering audience exposure and shaping perceptions. Similarly, [1] revealed how recommendation loops have directed users toward radical or partisan content, emphasizing that algorithmic mediation has tangible ideological consequences.

Recognizing YouTube as a sociotechnical system therefore compels researchers to examine not only user behavior but also the infrastructural logic that governs visibility. Algorithms serve as cultural gatekeepers, amplifying certain voices while silencing others, and thereby co-producing social hierarchies within the digital ecosystem. For creators, understanding these mechanisms is critical, as their success depends on navigating algorithmic preferences that prioritize engagement above all else.

Platform Capital: The Currency of the Creator Economy

Within this governed environment, creators accumulate platform capital—the platform-specific resources and reputational assets that enhance visibility and monetization potential. The most salient manifestation of platform capital on YouTube is the creator's subscriber base, typically operationalized as channel_follower_count. Subscribers represent a reservoir of guaranteed initial attention, which can be strategically leveraged to trigger algorithmic promotion of new uploads.

This dynamic exemplifies the Matthew Effect, or "rich-get-richer" phenomenon, observed in numerous digital contexts [16]. On YouTube, creators with large existing audiences enjoy cumulative advantages: their content generates early engagement, signaling relevance to the recommendation algorithm and thus increasing visibility in trending feeds. In contrast, creators with minimal audiences struggle to break this threshold, as lower engagement diminishes their likelihood of algorithmic exposure.

Empirical research supports this self-reinforcing cycle. Research [12] documented that viral video successes among small businesses not only boost short-term sales but also expand long-term subscriber networks, enabling subsequent videos to perform better through enhanced platform capital. Similar findings by [17] show that view concentration on YouTube is heavily skewed toward a minority of top creators, confirming the existence of entrenched inequalities. Consequently, visibility becomes both a cause and a consequence of accumulated audience size.

Weighing Capital Versus Effort: The Unresolved Gap

Existing literature converges on two critical determinants of digital success: accumulated platform capital and metadata optimization. Both contribute meaningfully to visibility, yet their relative importance remains empirically unsettled. Prior works acknowledge that subscriber count predicts baseline exposure, while metadata quality shapes searchability; however, few studies directly compare these factors within a quantitative modeling framework. As [10] note, most analyses rely on correlation or descriptive analytics rather than predictive modeling capable of ranking feature importance.

This absence of comparative quantification leaves an essential theoretical gap. When a new video is uploaded, does its success depend more on the creator's historical audience capital or on their real-time optimization efforts? Understanding this balance has implications not only for marketing strategy but also for digital inequality, since the dominance of audience factors would imply a system where past success entrenches future visibility. Conversely, if optimization can compensate for limited audience size, then creators retain agency through data-driven effort.

Recent advances in machine learning provide methodological tools to address this gap. Non-linear ensemble models such as Random Forest and XGBoost can capture complex feature interactions and assign relative importance scores, offering an empirical means of weighing capital against effort [11]. Applying these models to YouTube metadata enables researchers to test the hypothesis that audience size exerts a dominant influence over optimization features—a claim that, if confirmed, would substantiate critiques of algorithmic favoritism and attention inequality within the platform economy. In sum, the literature establishes a conceptual duality—platform capital versus optimization effort—but lacks quantitative reconciliation. The present study responds to this omission by integrating theories of sociotechnical governance, platform capital, and algorithmic legibility into a predictive modeling framework that measures their relative explanatory power in shaping virality outcomes.

Method

Figure 1 provides a flowchart of the research methodology, detailing the progression from feature engineering and target transformation to the comparative evaluation of the regression models.

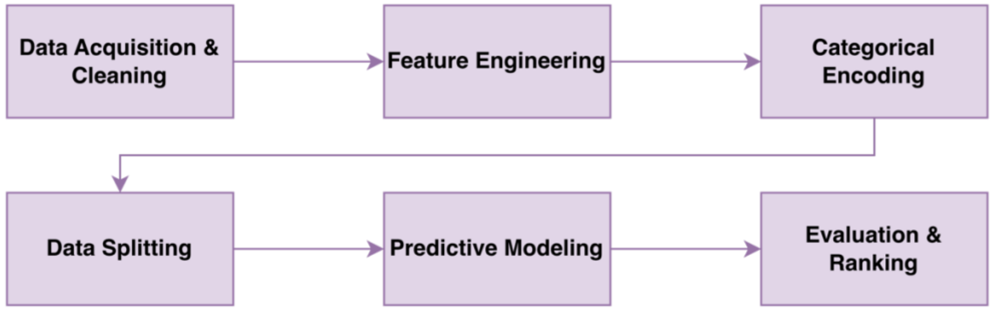

Figure 1 **Research Method Flowchart**

Research Design

This study adopts a quantitative, cross-sectional research design to systematically examine the determinants of YouTube video virality. The methodological approach centers on developing and evaluating supervised machine-learning regression models capable of predicting video popularity, operationalized as view count. The purpose is twofold: first, to achieve reliable predictive performance, and second, to identify and rank the metadata features that most strongly influence a video's success. This combination of predictive modeling and interpretive analysis ensures both analytical rigor and theoretical contribution. By leveraging computational techniques, the study aims to move beyond descriptive or correlational claims and to offer quantifiable evidence on the relative importance of audience-based and optimization-based factors. The overall research design, therefore, not only captures the statistical relationships among variables but also provides empirical grounding for the argument that a creator's pre-existing audience capital plays a dominant role in determining virality outcomes on YouTube.

Data Source and Preprocessing

The analysis utilizes the youtube-top-100-songs-2025.csv dataset from Kaggle, which contains metadata for the top one hundred music videos on YouTube in 2025. This dataset offers a representative snapshot of the contemporary digital music landscape and is particularly well suited for identifying patterns that distinguish highly successful videos from moderately popular ones. The processed version of this dataset, cleaned_youtube_data.csv, serves as the foundation for modeling. Prior to analysis, several preprocessing steps were implemented to ensure data quality and consistency. Numerical variables such as view_count, duration, and channel_follower_count were converted from text (object) to integer formats, enabling their inclusion in statistical and machine-learning models.

In addition to type conversion, several engineered features were created to enhance model interpretability. The description_length variable measures the number of characters in a video's textual description, reflecting the creator's effort in providing contextual information. The tag_count variable quantifies the number of tags associated with a video, representing keyword density and discoverability potential. A binary variable, is_official_video, indicates whether the title contains the phrase “Official Music Video,” distinguishing formal releases from fan uploads or alternate versions. The categories variable, which includes values such as “Music” and “People & Blogs,” was converted into numerical form through one-hot encoding to ensure compatibility with the models. These preprocessing procedures standardized the dataset, enabling both linear and non-linear models to process diverse data types while preserving interpretability across all features.

Variable Definition

The dependent variable in this study is view_count, which represents the number of times a video has been viewed on YouTube. Because view counts typically follow a power-law distribution—where a small subset of videos receives disproportionately high engagement—the variable was log-transformed using log(view_count) to approximate a normal distribution. This transformation reduces skewness, stabilizes variance, and improves both model performance and coefficient interpretability.

Independent variables were selected based on their theoretical relevance to platform success and were grouped into conceptual categories representing channel capital, content characteristics, optimization effort, and platform categorization. The channel_follower_count variable captures the creator’s accumulated audience capital and represents a long-term measure of influence within the platform. The duration and is_official_video variables describe intrinsic content characteristics that may affect viewer engagement or algorithmic promotion. Optimization effort is represented by description_length and tag_count, which quantify the creator’s deliberate actions to make the content more legible to YouTube’s recommendation system. Finally, categories represents the content’s placement within YouTube’s platform taxonomy, transformed into numerical indicators through one-hot encoding. Together, these variables provide a balanced framework for evaluating how both structural (audience-based) and behavioral (effort-based) factors contribute to virality.

Modeling and Analysis

The analytical process was conducted in three main stages designed to balance interpretability and predictive accuracy. The first stage involved the construction of a Multiple Linear Regression (MLR) model, which serves as a baseline for interpretability. This model quantifies the linear relationships between predictors and the log-transformed view count, allowing examination of coefficient direction, magnitude, and statistical significance. Through this model, the study identifies which features have a significant positive or negative association with virality and assesses whether audience-related variables maintain their expected dominance even under a linear assumption.

The second stage focuses on advanced modeling for predictive power. A Random Forest Regressor was implemented to capture non-linear relationships and complex feature interactions that may not be adequately represented by the linear model. As an ensemble-based approach, Random Forests combine multiple decision trees to improve generalization and reduce overfitting, making them particularly effective for datasets that contain both continuous and categorical predictors. This stage emphasizes predictive validity, assessing whether non-linear models provide superior explanatory performance over traditional regression methods.

In the third stage, model evaluation and feature importance analyses were conducted to determine the generalizability and interpretive value of the models. The dataset was split into an 80 percent training set and a 20 percent testing set to prevent overfitting and to ensure that model accuracy could be validated on unseen data. The R-squared (R^2) metric was used to measure the proportion of variance in log(view_count) explained by each model, while Root Mean Squared Error (RMSE) was employed to quantify average prediction error. To rigorously assess the divergence between the predicted view counts and the actual observed values, the RMSE metric is calculated. This metric penalizes larger errors more heavily than smaller ones, providing a conservative estimate of the model's predictive precision. Mathematically, for a set of *n* test samples where y_i represents the actual log-transformed view count and $\hat{y_i}$ represents the predicted value, the RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}$$

Lower values of this metric indicate a closer fit of the regression line (or hyperplane) to the data points, serving as the primary criterion for comparing the performance of the linear baseline against the non-linear Random Forest model. The Random Forest model additionally generated feature importance scores—computed through Gini or permutation importance measures—that quantify the relative contribution of each independent variable to the model's predictive accuracy. This ranking forms the empirical foundation for answering the study's central research question regarding whether audience size or optimization effort exerts greater influence on video virality.

Result and Discussion

Overview of Data Exploration

The dataset, comprising metadata from the top 100 most-viewed YouTube music videos of 2025 from Kaggle, was successfully imported, cleaned, and preprocessed prior to analysis. Exploratory data visualization confirmed several key characteristics of the dataset. The distribution of view_count was found to be highly right-skewed, indicating that a small number of videos attracted disproportionately large audiences. Applying a logarithmic transformation to view_count effectively normalized the distribution, mitigating skewness and ensuring that the assumption of homoscedasticity required for linear modeling was better satisfied. The correlation heatmap revealed moderate to strong positive associations between channel_follower_count and view_count, while other variables, such as description_length and tag_count, exhibited weak or negligible linear correlations. This preliminary observation suggested that audience size might play a more decisive role in determining virality than metadata optimization features.

Multiple Linear Regression (Baseline Model)

The first stage of the analysis involved developing a Multiple Linear Regression (MLR) model to establish a baseline for interpretability and comparison. The model used log(view_count) as the dependent variable and included channel_follower_count, duration, is_official_video, description_length, tag_count, and categories as independent predictors. The resulting model achieved an R-squared (R^2) value of –0.0680, indicating that it explained virtually none of the variance in the dependent variable. In fact, the negative R^2 suggests that the model performed worse than a simple mean-based prediction, implying that the linear assumptions of the model were inadequate for capturing the underlying relationships among variables. The Root Mean Squared Error (RMSE) on the log-transformed scale was 1.0970, further confirming poor predictive accuracy.

Visual inspection of the MLR actual-versus-predicted plot (figure 2) revealed a scattered, non-linear pattern with no discernible alignment around the diagonal line, which represents perfect prediction. This dispersion confirms that the linear model failed to capture the non-linear interactions and hierarchical relationships typical of social-media data, where success is often driven by exponential exposure effects rather than additive trends. These findings demonstrate the limitations of using traditional linear approaches to model YouTube virality, thereby justifying the transition to a non-linear ensemble method for improved predictive capability.

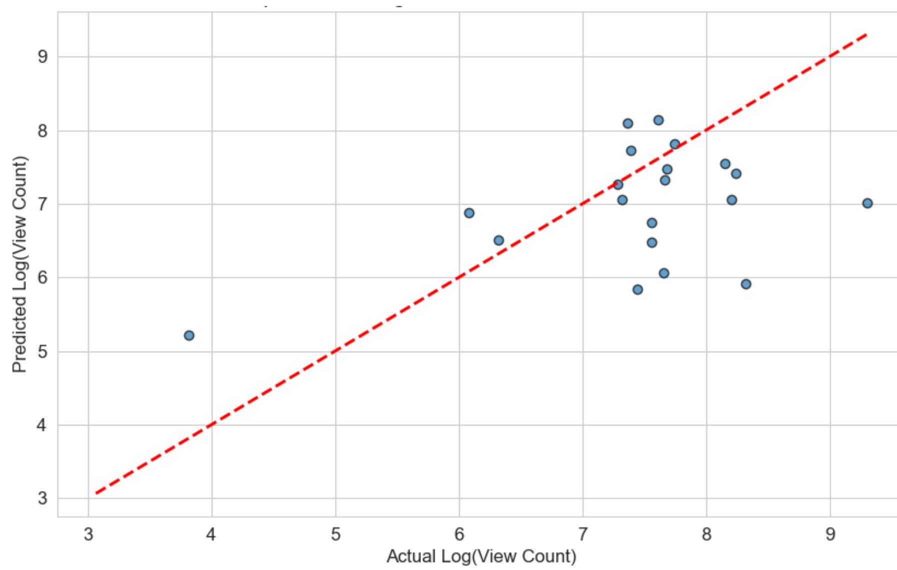

Figure 2 **Actual vs Predicted Views of MLR Model Plot**

Random Forest Regression (Advanced Model)

To address the inadequacies of the linear model, a Random Forest Regressor was trained using the same set of predictors. The model demonstrated substantially superior performance, achieving an R-squared value of 0.7157 on the test set, indicating that approximately 71.6 % of the variance in log(view_count) could be explained by the model. The corresponding RMSE was 0.5660 on the log scale, representing a considerable reduction in error relative to the MLR model. The model's out-of-bag (OOB) score of 0.7051 further validated its robustness and generalizability, suggesting that it was neither overfitted to the training data nor overly sensitive to noise.

The actual-versus-predicted plot for the Random Forest model (Figure 3) showed a strong alignment along the diagonal, with minimal residual variance. This indicates that the ensemble approach effectively captured the complex, non-linear dependencies among the predictors. The improved fit demonstrates that interactions between variables—particularly between channel-level and metadata-level features—are best modeled using non-parametric algorithms that do not rely on linear assumptions. Overall, the Random Forest results confirm that YouTube video performance is governed by multi-factor dynamics that are non-additive in nature, consistent with the study's conceptual framing of virality as a sociotechnical outcome influenced by both audience capital and optimization behavior.

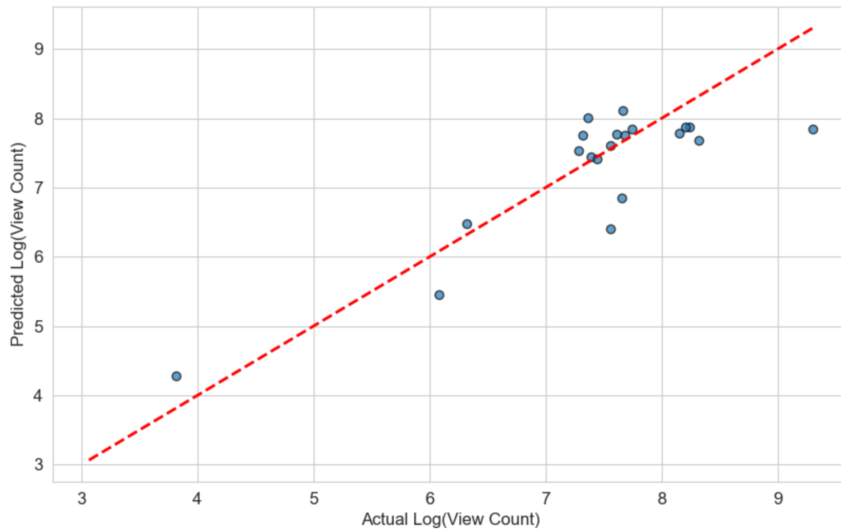

Figure 3 **Actual vs Predicted Views of Random Forest Model Plot**

Feature Importance Analysis

Beyond prediction accuracy, the Random Forest model's internal feature-importance metrics provided quantitative insight into the relative influence of each predictor on video virality. The feature-importance ranking revealed that channel_follower_count was, by a large margin, the most influential variable in predicting view_count. Its importance score substantially exceeded those of all other features, underscoring the dominant role of pre-existing audience capital in determining viewership outcomes. The next most relevant features, duration and is_official_video, contributed moderately to model accuracy but with significantly smaller weights. These variables likely reflect content and branding characteristics that influence user engagement at a secondary level.

Conversely, variables associated with metadata optimization, such as description_length and tag_count, displayed minimal importance in the model, suggesting that creators' efforts to optimize textual metadata had limited predictive value once audience size was accounted for. The categories variable also ranked low in importance, indicating that the general content classification (e.g., "Music" vs. "People & Blogs") contributed little to the prediction of virality within this dataset. These results empirically substantiate the study's central thesis: that audience-based variables exert far greater influence than optimization-based ones in shaping a video's success trajectory.

Comparative Model Evaluation

The performance comparison between the MLR and Random Forest models highlights the necessity of employing non-linear approaches in studies of digital virality. The MLR model's negative R^2 value (–0.0680) and high RMSE (1.0970) indicate that linear assumptions fail to capture the exponential dynamics of online popularity. In contrast, the Random Forest's R^2 of 0.7157 and RMSE of 0.5660 represent both statistical and practical improvements, demonstrating that ensemble learning provides a more accurate and realistic approximation of audience behavior. This comparative evaluation not only validates the analytical approach but also supports the theoretical premise that YouTube virality operates within a non-linear, feedback-driven ecosystem. Success on the platform cannot be explained by isolated metadata characteristics or incremental optimizations alone; instead, it arises from compounding audience effects that amplify exposure in an exponential manner. Consequently, creators who already possess substantial subscriber bases are structurally advantaged, as their videos are more likely to receive immediate algorithmic boosts through early engagement signals.

Feature Importance Visualization

Figure 1 presents the feature importance ranking derived from the Random Forest model, illustrating the relative contribution of each independent variable to predicting log(view_count). The horizontal bar plot visualizes each feature's importance score, which reflects how much that variable reduces prediction error across the ensemble of decision trees. As shown in figure 4, channel_follower_count overwhelmingly dominates the model, with an importance score of approximately 0.80, far exceeding all other predictors. This result demonstrates that a creator's existing audience base is the most decisive factor in determining video virality. It suggests that channels with large subscriber counts are structurally advantaged in accumulating views, as their uploads immediately reach a pre-established network of engaged viewers. The prominence of this feature provides strong empirical support for the concept of platform capital, wherein accumulated audience resources translate directly into algorithmic visibility and engagement potential.

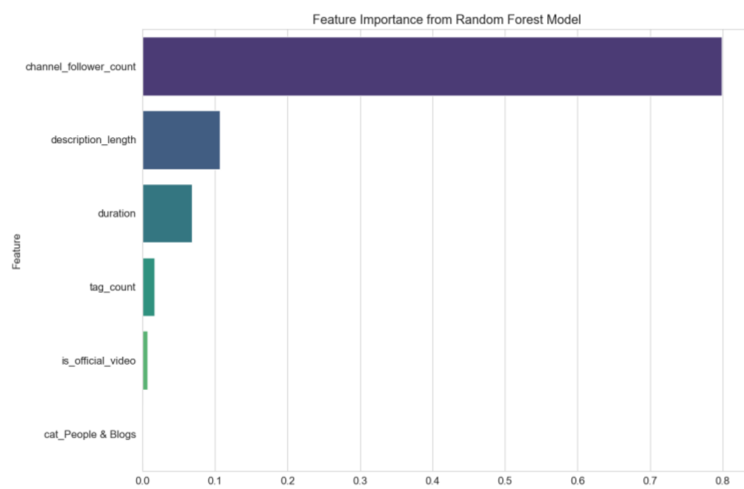

Figure 4 Feature Importance of Random Forest

The second most influential variable is description_length, with a substantially smaller importance score (around 0.10), followed by duration (≈ 0.07). These results indicate that while longer descriptions may modestly enhance discoverability—possibly by improving algorithmic legibility or providing richer contextual cues—their impact remains secondary compared to audience size. The remaining features—tag_count, is_official_video, and cat_People & Blogs—contribute negligibly to predictive performance, each registering importance scores below 0.03. This confirms that metadata optimization and categorical placement play only marginal roles once the effect of channel audience is accounted for. Overall, figure 4 visually encapsulates the central finding of this research: YouTube virality is disproportionately determined by a creator's pre-existing audience capital rather than by content-level optimization efforts. The steep decline in feature-importance values from channel_follower_count to all other variables underscores the dominance of audience factors within the platform's algorithmic ecosystem. This pattern aligns with the theoretical premise of the "Matthew Effect," in which success on digital platforms accumulates exponentially among those who already possess substantial attention capital.

Discussion

The results of this study provide strong empirical evidence that YouTube video virality is primarily driven by a creator's pre-existing audience capital rather than by short-term metadata optimization efforts. The Random Forest model, which explained over 70% of the variance in log(view_count), clearly demonstrated that channel_follower_count was the most influential predictor by a substantial margin. This finding aligns with theories of platform capital and the Matthew Effect, both of which describe how prior success accumulates into future visibility advantages in digital ecosystems. On YouTube, creators with larger subscriber bases are not merely advantaged in exposure but are algorithmically reinforced through engagement loops that privilege their content in recommendation systems.

The secondary influence of description_length and duration suggests that while creators' optimization efforts contribute marginally to discoverability, their effects are dwarfed by the power of audience capital. Metadata optimization, such as increasing tag density or refining descriptions, may improve visibility within niche contexts but cannot compensate for the structural dominance of established channels. These results reinforce the argument that virality is a sociotechnical outcome — shaped as much by platform design and algorithmic governance as by creator agency. In essence, the architecture of YouTube promotes cumulative advantage, rewarding creators who have already amassed attention and engagement, while limiting the visibility of newcomers who lack existing capital.

Limitations

Although the findings are robust, this study is subject to several limitations. First, the dataset comprised only the top 100 most-viewed music videos of 2025. While this scope ensured a focused analysis of high-performing content, it may not fully represent smaller channels or non-music categories. A larger dataset covering multiple genres and performance tiers would provide more generalizable insights. Second, the study relied exclusively on publicly available metadata; variables such as viewer demographics, engagement ratios (likes, comments), and watch-time retention could offer a more nuanced understanding of virality dynamics but were unavailable within the dataset. Third, given the cross-sectional design, causal inferences cannot be drawn — the models capture correlation and predictive patterns rather than direct causation. Finally, algorithmic parameters on YouTube evolve continuously, and the relationships observed in 2025 may shift as the platform modifies its recommendation and ranking systems.

Future Research

Future studies should extend this research by integrating temporal dynamics and behavioral data to model how audience engagement evolves over time. Longitudinal approaches could track the growth trajectory of new channels to determine when and how audience capital begins to exert dominant influence. Additionally, expanding the analysis across multiple platforms — such as TikTok, Spotify, or Instagram Reels — would help determine whether the dominance of platform capital is a universal phenomenon or specific to YouTube’s architecture. Future research could also explore causal inference using methods such as Granger causality or structural equation modeling to disentangle the directionality between audience size, algorithmic exposure, and virality. Moreover, qualitative approaches, such as creator interviews, could complement quantitative findings by revealing how creators perceive and strategize around algorithmic visibility.

Conclusion

This study quantitatively demonstrates that the anatomy of YouTube virality is overwhelmingly dominated by audience capital. Through the application of machine-learning models to metadata from the top 100 YouTube music videos of 2025, it was found that channel_follower_count far outweighs metadata optimization variables such as tag_count and description_length in predicting view counts. The Random Forest model achieved strong predictive accuracy, confirming that virality operates through non-linear, cumulative processes best explained by feedback-driven engagement mechanisms. These findings underscore the systemic inequality embedded within digital platforms, where success reinforces success and visibility is algorithmically concentrated among creators with existing audiences. For aspiring creators, the results highlight the strategic importance of cultivating loyal subscribers and cross-platform branding, as algorithmic optimization alone yields limited results. For researchers and policymakers, the study contributes to the broader discourse on platform governance, algorithmic accountability, and digital labor, illustrating how algorithmic systems privilege accumulated capital over creative effort. Ultimately, YouTube’s virality reflects not an equal contest of creativity, but a feedback system that magnifies pre-existing influence within the digital attention economy.

Declarations

Author Contributions

Conceptualization: N.C.R.; Methodology: N.C.R.; Software: S.F.; Validation: N.C.R.; Formal Analysis: N.C.R.; Investigation: S.F.; Resources: N.C.R.; Data Curation: N.C.R.; Writing Original Draft Preparation: N.C.R.; Writing Review and Editing: S.F.; Visualization: S.F. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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