Does the early audience evaluation in 2022-measured as IMDb rating and rating count-have a delayed effect on a film's popularity-measured as the number of views per title-on Netflix in the second half of 2023?

Word count: 1699

Page count: 4

Introduction

Netflix has been regarded as a pioneer in film and television streaming over the past decade and remains one of the largest mainstream streaming platforms. Since entering the film and television industry in 2007, it has significantly reshaped the industry's distribution model and business logic by both licensing content from other production companies and funding its own original films and series (Ulin, 2019, p.336; Wayne, 2021). With 301.64 million subscribers in the fourth quarter of 2024, Netflix continues to demonstrate strong profitability (Netflix, 2025). As streaming platforms have become a major distribution channel for film and television content, understanding the factors that influence a work's popularity on such platforms is crucial for both content creators, platform operators and marketers alike.

When selecting the study's variables, IMDb's film and television ratings and the number of user ratings were chosen as one of the key reference variables due to its vast scale of film and television listings (23.34 million) and the volume of user ratings (8.44 million) (IMDb, 2025).

Research Question

This study aims to investigate the extent to which two variables—IMDb rating and the number of ratings per film—as recorded in 2022, influence a title's popularity on Netflix, measured as total views between July and December 2023 per title. Variables and data outside this defined temporal scope fall beyond the remit of this research. More specifically the study examines whether there is a delayed effect of rating data on subsequent viewer behaviour. It further explores whether there is a significant interaction effect between a film's rating and the volume of ratings it receives, which may jointly influence viewer engagement.

Hypotheses

H_0: Prior audience evaluation—measured by a film's IMDb rating, rating count, and their interaction (as of 2022)—has no significant effect on the film's popularity on Netflix—measured as total hours viewed divided by runtime in the second half of 2023.

H_1: Prior audience evaluation—measured by a film's IMDb rating, rating count, and their interaction (as of 2022)—significantly affects the film's popularity on Netflix—measured as total hours viewed divided by runtime in the second half of 2023.

Literature Review

Review, Rating and Market Performance

Souza, Nishijima and Fava (2018) found that the larger and more positive the volume of professional reviews and user ratings, the longer a film tends to remain in theatres. Ulin (2019) indicated that box office revenue still accounts for the largest portion of profits for most films, and a longer theatrical run contributes to better market performance. However, Moon, Bergey and Iacobucci (2010) discovered that strong early market performance can in turn positively influence overall rating (both professional and user review) performance.

These studies attempt to demonstrate a potential positive correlation between film market performance and the positive ratings. However, they all, to some extent, overlook the fact that positive market performance and favorable media reviews may be part of a film's promotional strategy, and the observed correlation could be a result of deliberate manipulation. Moreover, research linking ratings and market performance has largely focused on theatrical releases, while studies examining streaming platforms remain limited. Therefore, this study aims to explore the relationship between user ratings and the market performance of films on streaming platforms.

Delayed Effects of User Ratings on Streaming Behaviour

The mechanism between market feedback and evaluation has long been widely studied in fields such as consumer psychology and marketing. Among these studies, one of the commonly-applied theoretical frameworks is the Stimulus–Organism–Response (S-O-R) model. Originally proposed by Mehrabian and Russell (1974), the S-O-R framework is a model in psychology that describes how external stimuli (Stimulus) trigger specific behavioural responses (Response through the mediating role of an individual's internal state (Organism).

In many studies applying this framework, the internal processing stage (O) is described as an independent cognitive or affective process. For instance, in the context of online retail, Eroglu, Machleit, and Davis (2001) used the S-O-R model to discover that environmental cues impact consumers' internal evaluations, which subsequently influence their approach or avoidance behaviours. This suggests that “O” can involve a temporal delay between the initial stimulus and the response.

While such studies have laid the foundation for explaining time gaps between stimuli and responses, similar research in the film industry remains limited. Although some studies indicate that the overall rating trend as a stimulus can affect subsequent individual ratings (Moon, Bergey and Iacobucci, 2010), research on whether rating systems exert a measurable impact on the popularity of films on streaming platforms is still scarce. Given that many theatrical films are only released on Netflix after completing their cinema run, there is often a time lag between the release of ratings and the film’s availability. In this context, examining whether ratings have a delayed effect on a film’s popularity on streaming services becomes especially relevant. This study addresses this gap by examining whether user-generated ratings and rating volumes recorded prior to 2023 correspond with viewing outcomes during the first half of that year.

Presentation of Data

In this research, a film’s popularity on the Netflix platform is measured by its views in the second half of 2023, calculated as total hours viewed divided by runtime. The primary source for views data is Netflix’s officially published 2023 H2 Engagement Report, while data on IMDb ratings and rating counts are obtained from the open dataset platform Kaggle, where the dataset was compiled by scraping the IMDb database (Netflix, 2024; itisnarayan63, 2022).

Although both datasets cover a large sample size, only 644 films were ultimately selected for this research after filtering. Selected films must be globally available on Netflix and have a corresponding IMDb entry. Shorts, TV series, and film entries with incomplete data were excluded from the research.

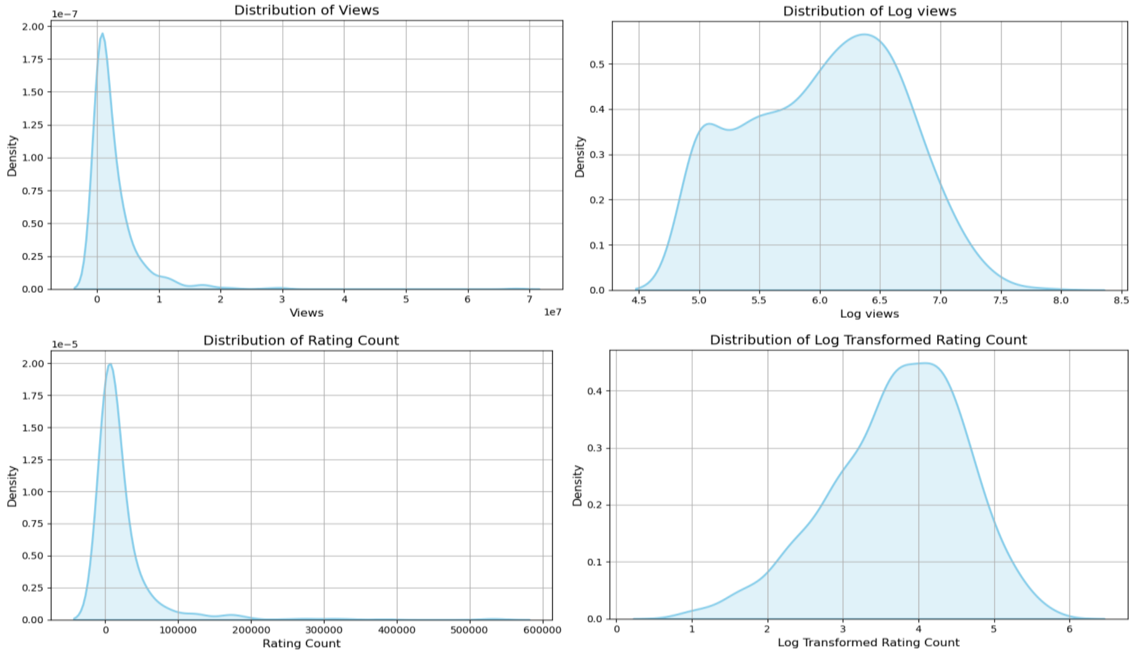


Chart 1. Kernel Density Estimation Plot of the Key Variables

Table 1. Summary Statistics of Variables Used

	Views	Rating	Rating Count	Log Transformed Views	Log Transformed Rating Count
Mean	2701863.35	6.15	23825.73	6.02	3.72
StdDev	4598995.39	0.97	52308.52	0.64	0.88
Minimum (Q0)	100000.00	2.60	9.00	5.00	0.95
Maximum (Q4)	67800000.00	9.00	538546.00	7.83	5.73
First Quartile (Q1)	300000.00	5.50	1387.50	5.48	3.14
Third Quartile (Q3)	3300000.00	6.80	22204.50	6.52	4.35
Median (Q2)	1200000.00	6.20	6380.50	6.08	3.80
Interquartile Range (IQR)	3000000.00	1.30	20817.00	1.04	1.20

From the KDE plots of the variables, it can be observed that both **Views** and **Rating Count** exhibit a highly right-skewed distribution. That is, the vast majority of values are concentrated at the lower end, while a very small number of films have exceptionally high views and rating counts. This distribution suggests that most films did not receive much attention, whereas a few titles attracted the vast majority of viewer engagement. After applying a base-10 logarithmic transformation to both view counts and rating counts, the distributions appear more symmetrical, significantly reducing the presence of outliers.

We can also tell that from the summary statistics, in which both variables display very high standard deviations, indicating an extremely dispersed distribution. However, after log transformation, the standard deviations decrease significantly, and the data become more evenly distributed.

Chart 3. Boxplots of the Variables

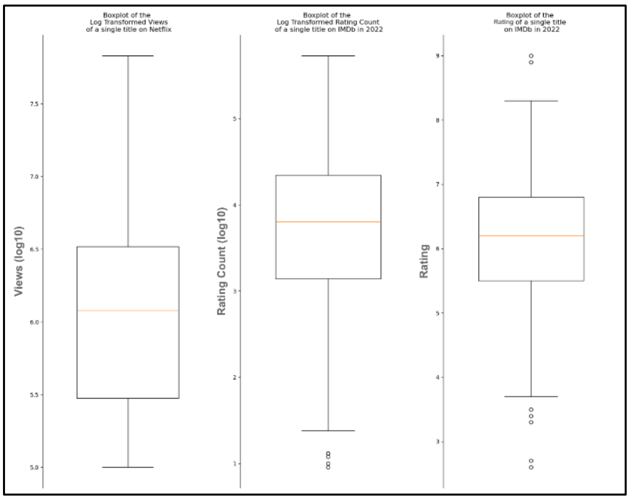
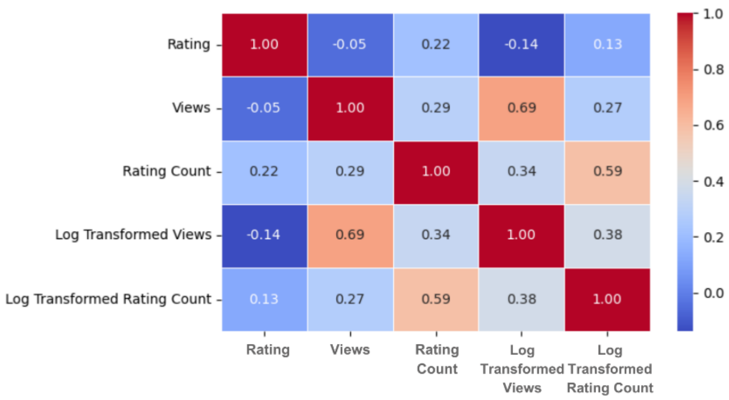


Chart 2. Correlation Heatmap of the Variables



Methodology

We employ a sample of 644 films in this research, utilizing multiple linear regression (MLR) to understand the extent to which IMDb rating, rating count influence a film's popularity on Netflix. MLR is a statistical method used to evaluate the relationship between multiple independent variables and a single dependent outcome variable in research (Marill, 2004). Given the highly skewed distribution of the original view and rating count data, a base-10 logarithmic transformation was applied. An interaction term between rating and rating count (their product) was also included as an additional independent variable.

Dependent Variable	Independent Variables
Log Transformed Views (***LogV***)	Log Transformed Rating Count (***LogC***) Rating (***R***) Interaction = LogC * R (***Int***)

The general form of the model applied to the data is:

$$LogV = \beta_1 LogC + \beta_2 R + \beta_3 Int + \epsilon$$

A series of standard diagnostic test were conducted to examine the validity of the model, including F-test for overall model significance and residential analysis to assess the model assumptions such as linearity, normality, and homoscedasticity.

Results

Table 2. Regression Statistics for Every Independent Variable

	Coefficient	Standard Error	t	p-value
R	β_1 = 0.143	0.095	1.500	1.340E-01
LogC	β_2 = 0.757	0.161	4.688	3.372E-06
Int	β_3 = -0.0735	0.025	-2.896	3.910E-03

β_1 represents the expected change in ***LogV*** when ***R*** increases by one unit, holding all other variables constant. Similarly, β_2 and β_3 reflect the respective influence of the other two variables on the dependent variable. According to Table 2, the p-values for ***LogC*** and ***Int*** are both below 0.05, indicating that these variables are statistically significant predictors. In contrast, the p-value for ***R*** exceeds 0.05, suggesting that its effect on the model is not statistically significant. The magnitude of β_2 is relatively large compared to the scale of the dependent variable, indicating that ***LogC*** has a strong positive effect on ***LogV***. Conversely, β_3 is smaller in magnitude, implying a slight negative influence from the interaction term. Overall, two out of the three independent variables demonstrate statistical significance.

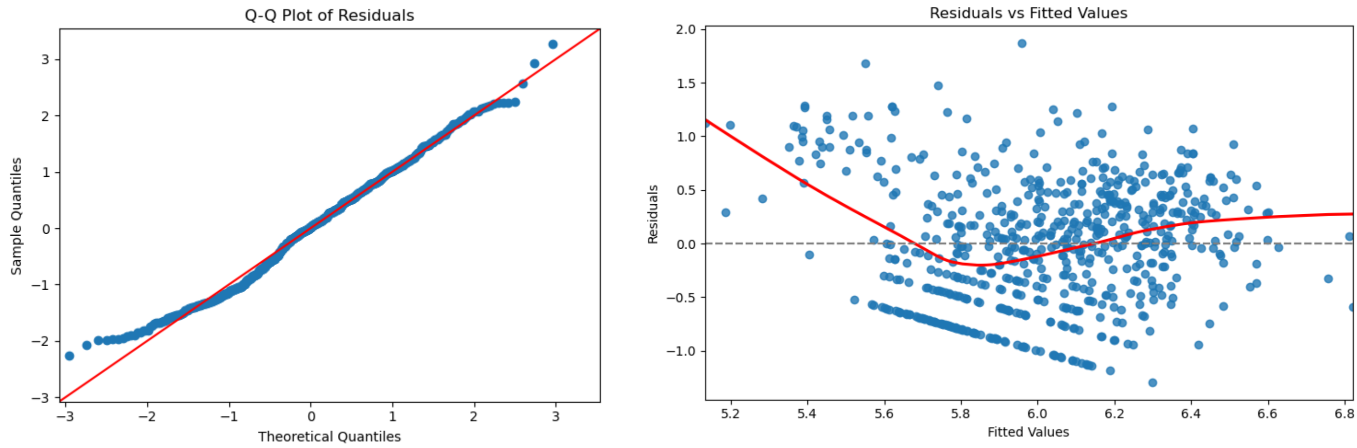
Table 3. Model Fit and Residual Diagnostics Statistics

R-squared	Adj. R-squared	F-statistic:	p-value (F-statistic)	Skew	Kurtosis	Jarque-Bera (JB)	Prob(JB)	Durbin-Watson
0.193	0.189	50.86	1.710E-29	0.16	2.48	9.79	7.48E-03	0.32

Based on table 3, the model explains approximately 19% of the variance in LogV, with an F-statistics of 50.86 and a p-value of $1,710e^{-29}$, which is much smaller than the 0.05 threshold and indicates the ovreall model significance. Therefore, the null hypothesis H_0 can be rejected, and implies that at least one of our chosen variables has impact on the films popularity on Netflix.

However, the residual diagnostics suggest certain limitation within this model. The relatively low Durbin-Watson statistic reveals strong positive autocorrelation in residuals, while the Jarque-Bera test indicates a statistically significant deviation from normality. The residual plots further support these findings with visible non-random patterns and mild skewness.

Chart 4. Residual Plots



Discussion

This study investigated how IMDb rating and the rating count per title affect a film's popularity on Netflix. According to the multiple linear regression model, the rating count (log-transformed) alone and its interaction with rating were significant predictors of the views of the film (log-transformed). The rating score by itself, however, was not statistically significant. Which suggests that a film's quality as perceived by a narrower audience does not independently count as a signal to predict popularity without a broader audience engagement to generate early audience evaluation.

The interaction term carries a surprisingly negative impact on the film's popularity, which may correspond with the diminishing marginal utility, as rating count increases, the influence of rating score on views slightly decreases (Gossen, 1983).

Although the corresponding statistics of the model allows the rejection of the null hypothesis H_0, the residual analysis exposed its violations in independence and normality assumptions, limiting the model's validity (Gujarati and Porter, 2009). It would be worthy to explore non-linear models or integrate more factors like duration and marketing budget in the future research.

Conclusion

Evidence has suggested that IMDb rating count and its interaction with rating can significantly shape a film's popularity on Netflix. The research confirms a partial explanatory relationship in this complex industry, though the mild violation with some of the regression assumptions may decrease its predictive accuracy.

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