**MASTER THESIS IN MARKETING ANALYTICS**

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# Behind the Streaming Video on Demand (SVOD) chart success of movies: An empirical investigation on the (synergistic) effects of emotional trajectories and scene volatility on movie performance


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## Management Summary

There remains no doubt that the entertainment industry has reached the pinnacle of success in the past few years. Particularly in the pandemic context, there have been previously unseen developments, such as an increase in the number of streaming subscriptions. Different from the traditional box office, the idea is that the consumer is the king on streaming platforms as they would have the choice to watch from the millions of movies available on the platforms.

On one hand, this has resulted in a shift in the film industry, particularly the subsect of films that were solely dependent upon the box office, as other digital platforms are now available. On the other hand, streaming service providers such as Netflix have captured a significant portion of the market. With this changing trend, another aspect has been changing drastically. The aspects which would determine the success or failure of a box office movie, do not necessarily have the same influence on the content on streaming services.

This research aims to disentangle the relationship between the chart success of movies along with six emotional trajectories (e.g., “Riches to Rags”, “Tragedy”, “Icarus”, “Man in a Hole”, “Cinderella”, and “Oedipus” emotional trajectory) and scene volatility. The extent of the impact as well as how to utilize these impacts to create movies that have better chances of succeeding have been discussed here.

The research starts with the dataset of the Top 10 Global Datasets that are available to the public. Then, a python script was built to consolidate the data by adding variables such as the production budget, ratings, and power of the cast members. Then, the movies were segregated as per the different emotional trajectories. The research showed that certain emotional trajectories showed a higher possibility of being perceived positively by the audience, whereas others were not quite easily acceptable. However, the current research is only foundational and opens up pathways for future research

**Preface**

The thesis "*Behind the Streaming Video On Demand (SVOD) chart success of movies: an empirical investigation on the (synergistic) effects of emotional trajectories and scene volatility on movie performance*" marks the final stage of my academic journey. Here I dedicate my gratitude to all the people who have supported me since the beginning.

First and foremost, I just want to thank my professor/supervisor, Dr. George Knox, for all the guidance. There is no word to express my appreciation for the countless time and effort he spent on reading, revising, and improving my work.

The second person I would like to extend my gratitude to is my professor/second assessor, Dr. Hannes Datta, from whom I got the chance to learn programming. Without his remarkable teaching, I could not have had the skills to successfully analyze such an extensive amount of data in this study.

Finally, to mom, the most important person in the world, I truly want to give this work as a present for her. It was the end of a long term, and it was sometimes hard to find the motivation to work on the thesis while completing all important courses. I would not have been able to do it without her unconditional love through my best and worst mental stages.

Once again, thank everyone for making this journey so much more meaningful!

Rotterdam,

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# Table of Contents

## 1. Introduction

The latest annual report from The Motion Picture Association sheds a light on a prevailing trend in the post-COVID-19 entertainment industry: the rapid growth in streaming video-on-demand (SVOD) services. The pandemic has accelerated consumers' adoption of streaming ever since many theatres, restaurants, and leisure attractions were closed to follow obligatory precautions against a COVID-19 infection. Accordingly, the number of streaming subscriptions in the United States increased to 308.6 million in 2020, and to another milestone of 353.2 million in 2021 (Motion Picture Association, 2021). Furthermore, the transition by consumers to SVOD services has not dissipated post-pandemic lockdown. As time spent consuming SVOD services continues to grow by 23.5 percent per year, studios in cooperation with SVOD providers are consistently pushing more streaming content online to make their services valuable to consumers (Hayes, 2022). For instance, in 2021, a total of 179 streaming exclusive movies were released, an increase of 58.4 percent compared to the preceding year (Motion Picture Association, 2021).

For studios, the SVOD market not only helped them pull through the loss of box office sales due to prolonged pandemic lockdowns but also created an increasing revenue stream alongside the theatrical entertainment market (Arkenberg et al., 2020). Yet, at the same time, it has posed a challenge in producing highly desirable streaming content. One major reason for this is that the surge of streaming services has provided consumers with the availability of diverse cinematic content, which has caused consumers' consumption and preferences to diversify (Datta et al., 2018). Moreover, studios did not have a lot of time to adjust to the fast-paced changes. Despite the fact that one of the main players, Netflix, invested $17 billion in licensing and producing content to catch up with the growing demand, only a small proportion of the releases delivered good performance (Low, 2021). The amount of quality content Netflix has offered is still not enough to satisfy consumers' evolving preferences (Rosney, 2022), given that the streaming provider reported a loss of a million subscribers in July 2022 (Sherman & Clayton, 2022). Thus, this has put new pressure on studios to predict what content will perform well before making a financial investment.

A recurring notion for determining or predicting box office success according to such drivers is that they tend to be external (e.g., star power and budgets) or post-production-related (e.g., online reviews). This has led to an argument that success in the entertainment industry is determined by social influence instead of by the products themselves (e.g., entertainment features of the movies; Salganik et al., 2006). Then what leads certain movies to pass through consumers' psychological processes and prosper around the globe, whereas some fall flat quickly?

Various scholars posit that how stories are written can shape what consumers feel and remember, which in turn influences how they respond afterward (Berger et al., 2012; Berger & Packard, 2018). For example, consumers are inclined to watch theatrical movies with happy endings over those that end in an emotional downfall (del Vecchio et al., 2021). In addition, stories which evoke strong emotions like arousal are more likely to be shared by consumers, thereby becoming popular (Berger, 2011; Berger & Milkman, 2012).

In recent studies on theatrical releases, the commonly deployed approach in these studies is using the binary sentiment analysis technique to uncover and visualize the emotional development audiences experience in movies. Then movies are partitioned into groups of similar shapes/trajectories (del Vecchio et al., 2021; Lee et al., 2017; Reagan et al., 2016). One study classified storylines of theatrical movies into six emotional trajectories, namely "Rags to Riches (rise)", "Tragedy (fall)", "Man in a Hole (fall-rise)", "Icarus (rise-fall)", "Cinderella (rise-fall-rise)", and "Oedipus (fall-rise-fall)". It was discovered that movies with the fall-rise emotion (Man in a Hole) are more likely to perform well at the box office (del Vecchio et al., 2021). Though this approach allows research to empirically quantify the influence of emotional trajectories on the success of motion pictures, it is worth considering how the influence of the emotional trajectories would play out in the presence of images in movies.

Besides emotional trajectories in movies, another feature that is theorized to crucially influence movie success is images (Green & Brock, 2000; Hennig-Thurau & Houston, 2019). Images or visuals in movies are postulated to facilitate viewers' engagement in the movies according to the narrative transportation theory (Green & Brock, 2000; van Laer et al., 2014). A prior study suggested rapid changes, changes in direction, or alternating between positive scenes and negative scenes can make images in movies more vivid, intense, and concrete (Cutting, 2016). Specifically, scene volatility is described to capture how frequently and how quickly movie scenes alter in direction, from a positive scene to a negative scene and vice versa (Berger et al., 2021). It was found that volatile stories can foster positive stress, hence keeping consumers stimulated and satisfied when consuming the stories (Etkin & Mogilner, 2016; Ladhari, 2007; Rietveld & van Beest, 2007). In the context of movie consumption, movies with many oscillations between positive and negative scenes keep people engaged till the end (Berger et al., 2021).

So far, the effects of emotional trajectories and scene volatility on movie success were investigated individually as a single independent variable (Berger et al., 2021; del Vecchio et al., 2021; Reagan et al., 2021). Previous research did not empirically consider the synergy of imagery and emotions to explain the entertainment consumption process and their effects on the success of movies. When considering the effect of emotional trajectories and scene volatility independently, we know that movies that steer audiences through different emotions tend to outperform those with one ongoing emotional direction (del Vecchio et al., 2021; Gerrig, 1993; Green & Brock, 2000) and more variation in scenes increases viewers' engagement (Berger et al., 2021). In the end, all of this translates to better performance on the SVOD chart. However, it is worth noting that an abundant combination of the "Man in a Hole" trajectory (emotional fall at the beginning but ending on a positive note) and high volatility in movie scenes may be overstimulating. Consequently, it may disrupt narrative transportation, ultimately hurting the chart performance (Galak et al., 2013). Taking all into account, in this study, we tested for both the independent and synergy effects of the entertainment features on the SVOD chart success of movies.

In light of this, the research objective is to examine the relationship between emotional trajectories, scene volatility, and the chart success of movies on SVOD platforms. To this end, the following research question was drafted:

*To what extent do the emotional trajectories and scene volatility extracted from movie screenplays influence the chart success of movies on SVOD platforms, and to what extent does the synergistic effect of the two features predict SVOD chart success?*

To uncover the issue, the following sub-research questions are formulated:

Theoretical questions:

1. What is the emotional trajectory in movies?
2. What is scene volatility?
3. How are emotional trajectories related to the chart success of movies?
4. What are the theories explaining the influence of scene volatility on the chart success of movies?
5. How does the relationship between emotional trajectories and chart success of movies depend on sentiment volatility?

Practical questions:

6. To what extent do emotional trajectories and scene volatility influence the SVOD chart success of movies?

7. To what extent does the synergistic effect of emotional trajectories and scene volatility on SVOD chart success of movies?
8. How can studios and SVOD service providers implement the current findings on Entertainment features of movie screenplays to produce movies that are likely to perform well on charts?

***Theoretical contribution***

From a theoretical standpoint, it is the objective of the study to strengthen the strand of literature in the following ways.

First, while external influential factors such as user and critic reviews, star power, or budget are constantly received the spotlight in the empirical study on movie success (Dellarocas et al., 2007a; Elberse, 2007; Elberse & Eliashberg, 2003; Karniouchina, 2011; Treme, 2010), little has been done to features within the movies themselves. Identifying or predicting box office hits and failures based on more traditional metrics has always been notoriously challenging, and more movies end up being financial busts than being profitable despite huge production and marketing budgets (Bielby & Bielby, 1994; Hennig-Thurau et al., 2006; Kashima, 2008). Since screenplays are the blueprints of every movie, rather than determining the success of movies solely based on exogenous factors, we aimed to extend the strand of literature by looking at the emotional trajectories and scene volatility in movies to formulate predictions about how long the movies survive on top charting (Toubia et al., 2019). Furthermore, this is the first study to empirically consider the interplay between emotional trajectories and scene volatility in movie performance.

Second, one distinguishable remark is that when determining the success of movies, the majority of literature so far has focused on the success of theatrical releases in terms of box office revenues (Hadida, 2009), rather than on SVOD-related metrics (e.g., total hours watched or number of days on Top 10). Therefore, not only did the study explore the effects of features extracted from movie screenplays, but we also ventured into a new context. In other words, the focal population of interest in this study is movies on Netflix Top 10 Global.

***Managerial contribution***

Given the risky but growing nature of the SVOD market, depending on human experts to elect the "most likely to be successful" movie screenplays has been known as a labor-intensive task (Eliashberg et al., 2007). Especially, if counted exclusively those submitted in Hollywood, there is a steady inflow of 50,000 movie screenplays coming in every year (Meslow, 2011). Only a small fraction of those makes it through the greenlighting phase (i.e., received permission to start film production); and among these greenlighted movies, seven out of ten movies end up being a flop (Vogel, 2011). This implies that human evaluation of the piling of screenplays is susceptible to errors like accidentally turning down good-quality screenplays while passing the bad ones. The study offered screenplay writers, production studios, as well as streaming service providers practical implications on processing and utilizing emotional trajectories and scene volatility at a large scale to make movies more engaging. The reason why this might be beneficial for the three parties is that we shifted the perspective to audiences' to make a production decision. Here our findings uncovered which emotional trajectories are likely to transport audiences into the movies and how volatile the movie scenes should be to keep them continue watching. By improving consumer engagement, the movies are inclined to hit the Top 10 chart for a long period.

## 2. Literature Review

In this chapter, we provide an overview of relevant literature on the subjects in this study. We first cover all theories and empirical research that address the effects of emotional trajectories (section 2.1.) and scene volatility (section 2.2.). Following the comprehensive review on the two main independent variables, the study will further elaborate on the rationale behind inclusion of control variables. And before closing the chapter with hypothesis justification (section 2.5.), several theories related to the chart success of movies are presented in section 2.4.

### 2.1. Six emotional trajectories (arcs) of movies

Several theories have elucidated different motivations behind why people watch movies to understand which features of movie screenplays would keep consumers engaged in the narrative. The mood management theory or the hedonistic principal postulated consumers' movie choices are driven by the need to experience pleasurable emotions and to escape from unpleasant situations (i.e., consumers may seek to immerse in positive emotions or an intermediate level of ambivalent feelings so they can distract from distressing thoughts; Hirschman & Holbrook, 1982; Zillmann, 1988). Building upon the notion, Grodal (1999) suggested each movie genre is characterized to evoke certain central emotions; for example, people seek sadness and sympathy from tragedies, and particularly audiences associate the experience of intense and conflicting emotions with drama and horror movies (Appel, 2008; Maio & Esses, 2001; Oliver, 1993). This laid the foundation for the first line of research exploring the link between the emotional features of movies and their success (Knobloch-Westerwick, 2006). Drama or horror movies are more likely to be evaluated positively by consumers if they successfully elicit the genre-specific emotions as intended (Nalabandian & Ireland, 2019; Oliver et al., 2000). In a similar vein to the comedy genre, the level of happiness in comedy movies' trailers has a positive impact on consumers' watching intention which is a significant indicator of box office performance (Liu et al., 2018).

While the central emotion of a movie helps explain the rationale behind the media choices of individuals, it might overlook important nuances in different states of emotional experience in the movie which are likely to affect viewer engagement. To understand the complexity of emotions in motion pictures and their impact on audiences, it is essential to look back at the art of storytelling. Many centuries ago, Aristotle (1961) proposed that compelling stories should be able to offer emotional journeys to audiences through a three-act structure (i.e., a beginning – middle/peak – and ending). Stories told in the movies are similar to how a sequence of causal events unfold in real life, and each change or transformation a character undergoes prompts an emotional response from the viewers (Moss & Wilson, 2020). From a psychological lens, the purpose of moving audiences from one to other emotions is to transport audiences into the state of being immersed in the story (Gerrig, 1993; Green & Brock, 2000; Winkler et al., 2022) and meta-analytic evidence demonstrated that narrative transportation crucially pertains to the level of enjoyment (van Laer et al., 2014) and social sharing intentions (Winkler et al., 2022). In other words, movies that engender narrative transportation are likely to be recommended by consumers to others and are likely to increase the demand for sequels or prequels (Green et al., 2004). In the end, all of this contributes to movies' financial performance.

Some early work focused on measuring the magnitude of emotions at some specific moments in the movie such as the starting point of the movie, the middle, and the end since these moments are more prominent and more likely to evoke the strongest emotional response (Baumgartner et al., 1997; Kahneman et al., 1993; Plantinga, 2009). However, at this point, it is worth noting that it remains questionable which combinations of emotions (i.e., positive opening – positive peak – positive ending, or negative opening followed by a continuous rise in emotion in the middle till the end of the movie) engross consumers in the movie storyline better. This concern was later empirically tested on novels and theatrical releases by Reagan et al. (2016) and del Vecchio et al. (2021) respectively.

In the theoretical work of Vonnegut (1981), the author argued that every emotional change either up or down in the protagonist's journey can be shaped into a certain trajectory; in fact, many stories follow the same emotional trajectory. Following Vonnegut's methodology, recent studies have successfully visualized the emotional content of novels and movies on a massive scale by plotting stories in a two-dimensional space where the x-axis represents the beginning – the end of the narrative, and emotionality is displayed on the y-axis (del Vecchio et al., 2021; Reagan et al., 2016). Furthermore, not only did the authors partition movies into six emotional trajectories which are depicted in Figure 1, but they also bolstered the impact of emotional trajectories in movies on various success outcomes, namely revenues, audience engagement, and satisfaction levels (del Vecchio et al., 2021).

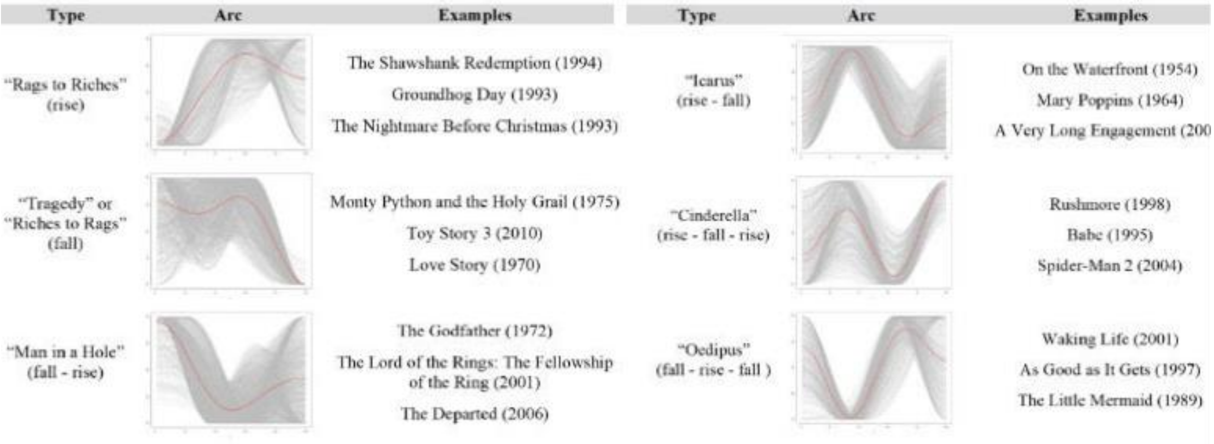



**Figure 1: Six emotional trajectories of movies (del Vecchio et al., 2021)**

Their results indicate movies that steer audiences through different emotions tend to outperform those with one ongoing emotional direction; for instance, the "Man in a Hole" cluster (which opens with an emotional fall but ends on a positive note) is positively related to financial performance, whereas the "Tragedy" cluster (an ongoing emotional fall to the end) is more likely to be unsuccessful in terms of revenues, consumer satisfaction (del Vecchio et al., 2021). An interesting pattern found in these studies is that (financially) successful emotional trajectories are necessarily the ones with the high review score, but they are the most discussed (i.e., reflected through the number of reviews online). This reinforces the proposition that dynamic development in emotional content enables audiences to be captivated by the narrative, and these people are inclined to disseminate post-consumption experiences to their social networks (Berger & Milkman, 2012; Green et al., 2004; Green & Brock, 2000).

### 2.2. Scene volatility

Besides emotions, another cornerstone of movie screenplays that is essential in movie consumption is images. Compared to other informing, educating, or entertaining vehicles like novels, motion pictures can tell people a story without the level of narration. It comes down to the distinguishing characteristic of movies. Movies show audiences what happens, whereas novels tell the story (Montgomery et al., 1992). In screenplay writing, one of the golden rules for successful movies is "show, don't tell", meaning characters' journeys or events should be described by the use of sensory details, actions, or images instead of narrative exposition (i.e., inserting descriptive background information within the story; Lubbock, 1955). According to Hennig-Thurau & Houston (2019), visuals in movies not only help contribute to the development of the narrative but also work as external stimuli enhancing transportation. Such an improvement in images facilitates audiences to reach an immersive state where they experience the told events along with the characters (van Laer et al., 2014). Several theories posit that audiences tend to remember vivid, intense, and concrete images longer than neutral ones (Lang, 1977; Lang et al., 1998; MacInnis & Price, 1987). Therefore, once images in movies are executed properly, it can foster narrative transportation which contributes positively to consumer engagement (Green & Brock, 2000; Green & Brock, 2002; Paulich & Kumar, 2021). Ultimately, research can utilize the mechanism to investigate the predictive power of imagery features from screenplay on the success of movies.

Screenplay literature has hypothesized that the rates of change, rapid changes in direction, or alternating positive and negative scenes can enhance the vividness, intensity, and concreteness of images which makes movies more engaging (Gergen & Gergen, 1988; McKee, 1997; Murtagh et al., 2009). Prior research has suggested using volatility to measure not only the number of times movie scenes change from one another direction but also the amplitude of scene changes (Berger et al., 2021). There are several reasons why oscillating between positive and negative scenes may be beneficial to increase audience attention in consuming movies.

First, volatility is pertinent to stimulation (McAlister & Pessemier, 1982; Pessemier & Handelsman, 1984). Studies on hedonic consumption like eating food, listening to music, and participating in physical activity showed that people tend to get bored of experiencing the same thing repeatedly (Ratner et al., 1999; Rolls et al., 1981). Nevertheless, when adding more activity variety to a one-hour event, the research found that this stimulates participants, which in turn prolongs the engagement level (Etkin & Mogilner, 2016).

Second, scene volatility enhances the vividness and intensity of images (Cutting, 2016). As it has been suggested that vivid, intense, and concrete images can engross audiences into a transportive state (Paulich & Kumar, 2021), this means movies with many changing scenes from positive to negative ones may keep viewers on the hook.

Third, Berger et al. (2021) evinced viewers' being engaged in a movie could be driven by uncertainty reduction. Besides stimulating people, volatility makes them feel uncertain about how the movie narrative will develop. In such circumstances where uncertainty arises, people have the tendency to take actions to reduce it, such as information seeking (Bruner, 1973; Kuhlthau, 1993). In the context of movie consumption, one of the information-seeking behaviors being observed is the continued consumption of stories (Berger et al., 2021). Therefore, one could argue that when watching movies with more volatile scenes, consumers are more likely to keep viewing to find out how things unfold.

### 2.3. External factors driving chart success of movies as control variables

Another core area that determines the SVOD chart success is understanding the consumers. Gen Z (i.e., people born from 1995 onwards) is the first generation to grow up with the internet. It dominates online content consumption behaviors, including online purchases at home (La, 2022). Analyzing the media usage behavior of Gen Z is a crucial factor in determining the SVOD chart success, as Gen Z is one of the major consumers of SVOD services. However, with various SVOD services, there is a need to reassess the core strategies that drive the success of movies released on SVOD. The critical factors of SVOD chart success, as highlighted by La (2022), include content, and marketing. Content success is attributed to a set of variables that include genre, star power, content authenticity, exclusivity, and novelty. For Gen Z, the content design, structure, or form should ensure quality and consistency. This also includes the overall user experience with SVOD platforms. Content adaptability when accessing services from different devices, access speed, and ease of service use are some of the essential technological factors comprising the design/structure of SVOD. They prefer to leave services/products/apps that are lagging or error prone. There is a high demand for anything that provides instant gratification. Marketing the SVOD services to the right audience will determine long-term success. Social media platforms, advertising, and influencer marketing are some of the most common strategies to attract a young audience. A huge marketing and promotion budget helped Netflix to gain immense profits in its first year (Kumar et al., 2020). Distribution determines how, where, and by whom the content distribution takes place. Before making a purchase or consuming a service, Gen Z has already decided whether it's worth their time and money by discovering on YouTube the value of a particular service. Determining the consumer's preferences plays a huge role while distributing.

From the study above by La (2022), it is evident that external content factors such as star power influence the SVOD chart success of movies. Similarly, other factors that can attract more audiences are the post-production ratings/reviews acquired through social influence platforms (La, 2022). Furthermore, according to many studies, higher-budget movies tend to perform better and have more chances of success (Ho et al., 2009; Rubin et al., 2022). Movie budgets are often known to audiences, and a high-budget movie is expected to deliver quality service. Hence grasps more audience (Rubin et al., 2022). Due to these, this study employed three control variables, i.e., star power, IMDb ratings, and budget, as covariates.

### 2.4. Chart success of movies

As the movie industry is a complex and uncertain business (de Vany & Walls, 1999), operationalization enables an enhanced understanding of the procedures and phenomena by turning abstract concepts into measurable variables. This section of the study highlights the theory determining the chart success of movies. In particular, for the box office domain, many studies employed revenue or financial returns as a fundamental factor in choosing a movie's popularity (de Vany & Walls, 1999; Hadida, 2009). The frequently used variables determining a movie's success or hit factor include star power, budget, and word-of-mouth/social influence (i.e., user and critic reviews), and recently features of movie screenplay have also gained some attention (citation). Some studies have investigated the impact of one of the variables mentioned above. In contrast, others conducted in-depth research on the effects of the combination of these variables on box-office movie success. Some researchers have also found the relationship between two or more variables to determine the movie's hit probability.

DeVany and Walls (1999) studied the impact of star power on revenue generated/financial returns on a box-office movie. The study concluded that the presence of a star in a movie could increase dominance in two ways. Firstly, star power can help get more movie bookings at the opening. Secondly, the exceptional performance of the star can level up the revenues. Hence, star power can be equated to a movie's opening power depending on bookings and a movie's staying power depending on the star's performance in the movie (de Vany & Walls, 1999).

The variables determining the success of box-office movies may still apply to those released on SVOD platforms. This section details the theory behind the success chart of movies on SVOD platforms. Some variables that can predict the hit factor of a movie are similar for both, i.e., box-office movies and SVOD movies. The factors like user and critic reviews, production budgets, and star power determine the success of movies in general. The competition is tough for the movies on SVOD platforms as there are various movies for consumers to choose from. Different SVOD platforms have distinct methods to determine a streamed movie's success. A suitable example is Netflix which keeps track of trending movies using three parameters: starters, completers, and watchers (Dixon, 2019). Starters indicate the number of homes that watch a movie for 2 minutes or an episode of a series. Completers are the number of households that watch 90% of the movie or complete a show's season. Watchers depict the number of homes that watch an episode of a series or watch 70% of a movie. Hence for SVOD movies, the real power lies with the audience. Based on the movie, the audience decides on its success after watching it. This takes us to another hypothesis that the real star is the movie instead of the star power (de Vany & Walls, 1999), which diminishes a few weeks after opening. This research, therefore, focuses on analyzing the features of screenplays that contribute to a movie's successful chart performance. The two features that this study analyzes are a movie's emotional trajectory and scene volatility.

## 2.5. Research expectations

### 2.5.1. Effect of emotional trajectories on SVOD chart success

The independent variable that determines the SVOD chart success is the emotional trajectory of a movie. Del Vecchio et al. (2021) clustered a movie's emotional development into six emotional arcs that depict the rise/fall trajectory for the opening, middle, and ending. According to Del Vecchio et al. (2021), the arc-type "Man in a Hole" and "Cinderella" generated maximum box-office revenues. The study suggested that U-shaped emotional arcs performed financially better because the emotional ups and downs displayed in these movies engender narrative transportation. Furthermore, prior literature emphasized that when emerging in a time-limited environment consumers prefer to experience an emotional uplift at the end (Kahneman et al., 1993). This further explained why "Man in a Hole" and "Cinderella" emotional trajectories tend to be more successful than emotional trajectories with unhappy endings like "Icarus" and "Oedipus" even though they also steer audiences through different emotions. We expect that the same two emotional trajectories will perform well on SVOD platforms, and the rest trajectories are posited to negatively influence chart success.

**H1a: Movies with emotional trajectories resembling "Man in a Hole" and "Cinderella" shapes are positively related to SVOD chart success.**

**H1b: Movies with emotional trajectories resembling "Rags to Riches", "Tragedy", "Icarus" and "Oedipus" shapes are negatively related to SVOD chart success.**

### 2.5.2. Effect of scene volatility on SVOD chart success

Studies have shown that scene volatility (the rapid transition and stringing together the positive and negative scenes) makes the movie more engaging and stimulating (Berger et al., 2021; Gergen & Gergen, 1988). Listening to the same songs or eating the same food can become boring. Similarly, watching scenes with fewer variations can make spectators lose interest. Scene volatility brings variety and increase stimulation, enhancing audience engagement. Furthermore, in the streaming environment where abundant options of series are available for consumers to choose from, stories told in the movies should be as engaging as possible to keep consumers watching. One study found volatility not only stimulates but also makes consumers curious about what will happen next (Berger et al., 2021). Therefore, though consumers may start watching a movie because of recommender systems and popularity via the Top 10, we would argue whether they continue with the rest of the movie depends on how engaging it is. Moreover, since the Top 10 is ranked by total hours watched, the show has a better chance of staying on the chart if viewers stick with it to the finish. It worth noting that too much volatility could make the audiences overloaded, thereby existing the immersed state (Galek et al., 2013). This may diminish the success of movies on streaming platforms. This study, therefore, hypothesizes scene volatility has a positive effect but diminishing on SVOD chart success.

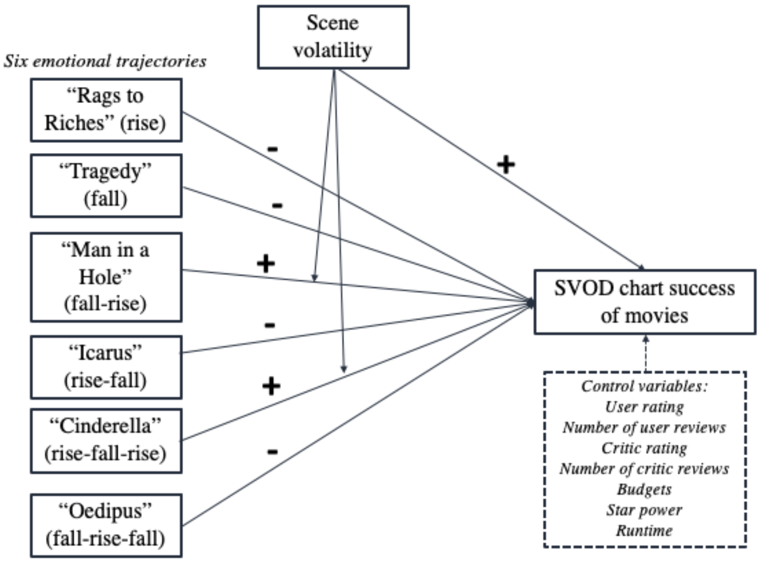
**H2: Scene volatility has a positive but diminishing effect on SVOD chart success**

Taking both individual effects of emotional trajectories and scene volatility into account, we can anticipate that the interplay of the two successful emotional trajectories and scene volatility is likely to boost movies staying on the Top 10 chart for a longer time.

**H3a: The synergistic effect of "Man in a Hole" trajectory and scene volatility is positively related to chart success, but the effect subsides as the movie scenes get more volatile**

**H3b: The synergistic effect of "Cinderella" trajectory and scene volatility is positively related to chart success, but the effect subsides as the movie scenes get more volatile**

### 2.6. Conceptual model




## 3. Methodology

This section entails the data design techniques engaging raw data collection, the analysis models, and tools. The study helps explain the mechanism driving the survival time of movies by performing natural language processing (NLP) analysis, cluster analysis on movie screenplays, and model fitting. Overall, the chapter first covers the detailed plan on how data are collected (section 3.1), then we further elaborate on the measurements of main variables as well as control variables in section 3.2. In section 3.2.1, we describe the k-mean method to partition movie screenplays into six emotional arcs which is a prerequisite for testing our final model. We close the chapter by presenting our log-log regression model (section 3.3).

### 3.1. Raw data collection

To examine the synergistic effects of movies' emotional trajectories and scene volatility on SVOD chart success, the data was compiled mainly from three data sources.

First, in terms of data on the chart success of movies on Netflix, we retrieved the Top 10 Global dataset directly from https://top10.netflix.com which has been collected by Netflix along with EY for public download since 2021. The sample covers from 28th June 2021 to 9th October 2022 with a total of 589 movies, of which 312 observations are English-spoken movies and the other 278 are non-English movies. One important remark is that since full access to all the records before the creation date is not feasible, the statistical inference in Chapter 4 – Results was based on the premise of non-probability sampling, specifically convenience sampling. The dataset contains limited but key information on each movie observation for scraping other independent variable-related data in the later stage. On the movie title level, we have records on the most recent weekly rank, the accumulated number of hours viewed, and the accumulated number of days in the Global Top 10.

In the second stage, we built a Python script to concatenate the Global Top 10 dataset with IMDb data by movie title. From the original Netflix dataset, several new variables were added such as unique movie ID, production budget, user and critic ratings, and list of nominated or award-winning casts.

Finally, to tackle the unavailability issue one may encounter when searching for screenplays, prior research utilized English subtitles from http://www.opensubtitles.com/ as a proxy for movie screenplays (Eliashberg et al., 2007; Tiedemaan, 2012). Furthermore, this allowed the study to analyze all non-English movies on Netflix. Regarding the retrieval of movie screenplays, we deployed a slightly different order than Berger et al. (2021), del Vecchio et al. (2021), and Paulich & Kumar (2021). As identifying the underlying emotional patterns in the motion picture is the focal point of these studies, the authors constructed the dataset by gathering every movie screenplay available online as a starting seed, then cross-checking and complimenting with data from other sources. Nevertheless, when using the movie titles to harvest the corresponding screenplays, we noticed that some movies have similar names, which might be resulting in incorrect file retrieval. As IMDb assigns a unique ID to each movie (e.g., Luckiest Girl Alive's movie ID is tt4595186, and Do Revenge's ID is tt13327038), these unique keys were compiled during the second stage and used as the next seeds to optimize search query in the request to http://www.opensubtitles.com/ instead. A detailed overview of all studied variables is displayed in Table 1.

Compared to Netflix and IMDb sources who gather information from the internal database, production studios, and filmmakers, the website http://www.opensubtitles.com/ is an open source where any users can contribute their subtitle works. For quality and reliability control, we only opted for subtitles provided by high-ranked users with the highest download volume and discarded the duplicates (Figure 2). Before proceeding with data transformation and analysis, an additional cleaning step was taken to ensure the format of the subtitle files follow that of movie screenplays. Any movie screenplays that have less than 2,000 words will be dropped (e.g., The Last Letter from Your Lover and 6 Underground). We omitted time stamps (e.g., 00:02:23,401 --> 00:02:25,790) and special characters that do not exist in the English alphabet or numbers, for instance, symbols and accent marks. Only 443 movies out of the total 589 made through the final cut.

| | Release name | Upload date | Release group | Uploader | ★ | | | |
|---|---|---|---|---|---|---|---|---|
| | Luckiest.Girl.Alive.2022.1080p.WEB.H264-NAISU HD | 2022-10-07 | | scooby74 platinum-member | 100% | 1 | 17331 | |
| | Luckiest.Girl.Alive.2022.1080p.WEB.H264-NAISU HD | 2022-10-07 | | scooby74 platinum-member | 0% | 0 | 6058 | |
| | Luckiest.Girl.Alive.WEBRip.Netflix HD | 2022-10-07 | | ghostwalker platinum-member | 0% | 0 | 4626 | |
| | Luckiest.Girl.Alive.2022.1080p.NF.WEB-DL.DDP5.1.Atmos.HDR.HEVC-CM HD | 2022-10-07 | | LordCosmos platinum-member | 0% | 0 | 1072 | |
| | Luckiest Girl Alive 2022 - 1080p NF WEB-DL x265 10bit HDR DDP5.1-CM HD | 2022-10-07 | | cvegah_ platinum-member | 0% | 0 | 1007 | |

**Figure 2: A snapshot of subtitles of the movie "Luckiest Girl Alive" sorted by user ranking and the number of downloads.**

### 3.2. Variable operationalization and transformation

#### 3.2.1. Clustering movie screenplays into emotional trajectories

To operationalize the six emotional trajectories proposed in the theoretical framework (Chapter 2), it is essential to grasp the core definition of the overarching term emotional trajectory. Originally coined by Vonnegut (1981), emotional trajectory in movies depicts the underlying emotional development that is designed to convey to audiences over a chain of causal-and-effect events. By tracing every change up and down in emotions as the narrative in movies unfolds and giving it a general shape, we can utilize the emotional trajectories as an indicator assessing whether a story is emotionally gripping enough to keep audiences emotionally invested in the narrative development or the protagonists' journey. And as has been discussed in the theory of narrative transportation, emotional involvement can foster audiences to be further immersed in the stories (Green et al., 2004), thereby positively influencing audiences' level of attention during consumption (Gable & Harmon-Jones, 2008), level of enjoyment (van Laer et al., 2014), and sharing intentions post-consumption (Winkler et al., 2022).

In the matter of constructing an appropriate number of emotional trajectories, some have theorized that there were around six to eight emotional trajectories (Vonnegut, 1981; Booker, 2004), whereas Tobias (1993) has suggested that stories could be partitioned into twenty distinguishing trajectories. Some recent empirical works have observed that at most six prominent trajectories could capture variation in movie narratives yet be able to provide parsimonious explanations for movie success (del Vecchio et al., 2021; Reagan et al., 2016). The six emotional trajectories in movie screenplays are described in Table 1.

The study underwent two phases to derive the six emotional trajectories. We first detected emotions in all 443 movie screenplays we had harvested in the raw data collection stage, then applied the k-mean clustering algorithm. In this study, we deployed a different emotional analysis approach than the proposed procedure in the papers of del Vecchio et al. (2021) and Reagan et al (2016). Particularly, prior research extracted and quantified positive or negative emotions from movie screenplays using either AFINN lexicon (i.e., a lexicon is a dictionary of words, each of which is associated with an emotionality score; Finn, 2011) or Linguistic Inquiry of Word Count (LIWC; Pennebaker et al., 2015) lexicon. We chose VADER lexicon (Hutto & Gilbert, 2014) to analyze emotions in movies instead. The rationale behind our decision is that VADER offers a much higher dictionary coverage of over 7,500 words than AFINN and LIWC, which cover 2,477 and 5,690 words respectively (Ribeiro et al., 2016). Besides the large lexicon size, VADER includes emotionality scores for features like word capitalization, punctuation, conjunctions, and degree adverbs, so the lexicon can differentiate the emotional magnitude between *"This is good."* and *"This is good!"*. Because of these improved features, VADER lexicon has been consistently shown to accurately identify positive, negative, and neutral emotions across different types of textual data (Ribeiro et al., 2016; Borchers et al., 2021).

For each cleaned movie screenplay, we iterated the process of partitioning the text file into sentences and running VADER package in R environment to assign an emotionality score to each sentence. The emotionality score is computed by normalizing the aggregated score of every word in the sentence so that the value falls within the range of [-1, 1], where -1 is the most negative emotion and 1 refers to the most positive one. Once we extracted emotions from the beginning to the end of the movie, the Discrete Cosine Transform (DCT) method (Syuzhet package) was implemented to smoothen the emotional pattern in each movie screenplay. The emotional trajectory of each movie screenplay was stored for cluster analysis.

In the second phase of deriving the emotional trajectories, the study adopted a k-means clustering algorithm instead of the hierarchical approach for several reasons. Based on the measurement by Reagan et al. (2016), there are at most six emotional trajectories that can be obtained from movie screenplays. This predetermined number of clusters can be used as a benchmark for this study to replicate and validate whether the emotional trajectories are robust in the SVOD context. And k-means is a good choice since we can specify the number of clusters needed to form (Steinley & Brusco, 2007). Different from hierarchical algorithms, we can generate and retain centroids (i.e., the centre point of a cluster) from the k-means model to further classify new movie observations to any emotional trajectory (Bouguettaya et al., 2015). Due to this nature of the k-means algorithm, we do not need to form whole new clusters again every time new data is included, which may change the cluster structure.

In order to train the k-means model to partition movies with similar emotional trajectories into one cluster, we used the "KMeans" algorithm in the Python library "scikit-learn" (Pedregosa et al., 2011). Behind the scenes, what k-means algorithm tries to solve is to minimize the variation within a cluster while maximizing the variation between a pre-defined number of clusters K, which as operationalized above is K = 6 emotional trajectories. The algorithm first initializes a set of K randomly selected data points as the centroids. From these initial centroids, each data point is assigned to the nearest centroid to form a group of similar data points, then new centroid values are computed. The whole calculation procedure will keep iterating until there is no change in the clusters and the centroids are stabilized (Mannor et al., 2011). So, let Within-Cluster Sum of Squares (WCSS) be the objective function that needs to be minimized:

$$\text{WCSS} = \sum_{j=1}^{K} \sum_{x_i \in S_j}^{N} (x_i - \mu_j)^2$$

Where,

WCSS captures the total variability in our movie data explained by the clustering results.

K denotes the total number of clusters we want to obtain, so the observations are partitioned into clusters $S_1$, $S_2$, ..., $S_j$.

N indicates the total number of data points.

$\mu$ is the centroid of cluster j.

$x$ represents the data point i in cluster j.

### 3.2.2. Scene volatility

We draw the operationalization of the scene volatility based on the definition and formula proposed by Berger et al. (2021). The scene volatility of a movie indicates the tendency to change quickly in scenes, taking into account the directions of change as well as the magnitude. It is calculated as the standard deviation (SD) of differences in valence between adjacent scenes. So, in comparison between a movie with high scene volatility and another with low scene volatility, it means that the former keeps oscillating back and forth from positive scenes to negative scenes more frequently than the latter. The formula is as follows:

$$Scene\ volatility = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(d_i - \bar{d}\,)^2}$$

Where $d_i = valence\ of\ scene_{i+1} - valence\ of\ scene_i$, $\bar{d} = \frac{\sum_{i=1}^{N-1} d_i}{N-1}$, and N is the total number of scenes. We also implemented the VADER lexicon to score each scene in a movie screenplay in the range [-1, 1], following the computation of scene volatility of that specific movie as the square root of the sum of squared differences (Berger et al., 2021).

To our knowledge, apart from the operationalization above, there are varying methods of quantifying changes in scenes, each of which has its own merits and demerits. For example, Paulich & Kumar (2021) measured the number of scenes a movie screenplay has as a signal for how quickly audiences are exposed to different scenes within certain runtimes. Nevertheless, this measure fails to consider that changes in scene directions also contribute to visual stimulation. Although a movie may show many different scenes if audiences keep seeing similar consecutive scenes such as five funny or action scenes in a row, then it still seems to be mundane and lacks stimulation. Alternatively, we have a similar measure to ours which instead takes the mean absolute deviation (MAD) of differences in valence between adjoining scenes to capture directional changes in movie scenes (Pham et al., 2001). Though both MAD and SD can show rapid changes in movie scenes as well as variations in directions, SD allows us to emphasize prominent changes in scene directions.

### 3.2.3. Chart success of movies

The focal measure of the chart success of movies on SVOD platforms is the number of days a movie stays on the Top 10 Global chart until it is overthrown by others. The chosen measurement is based on the work of Legoux et al. (2016) where the research operationalized the success of movies as survival time at the box office. SVOD service providers are known for not providing transparent metrics (e.g., domestic, or gross revenue) like traditional box office, they either withhold movie viewership data or develop their metrics such as total hours watched to compute Top 10 movies (Perez De Rosso, 2021; Seigel & Porter, 2021). For that reason, the number of days on Top 10 Global was observed as we drew an analogy between how popular movies are kept on screen for a longer time and how Netflix ranks its Top 10 list. Furthermore, the number of days on top charting is one of the success indicators for Netflix to determine renewals or cancellations (Moore, 2022). For example, recently the streaming provider decided to terminate the “Resident Evil" project because it could not survive in Top 10 after three weeks (Andreeva, 2022).

#### 3.2.4. Control variables

Due to the uncertainty in predicting what movies will become chart success, has led to a notion that the success of movies is driven more by social influence than by the movies themselves (Salganik et al., 2006). To fully capture the effect of emotional trajectories and scene volatility on the chart success of movies on streaming services, we observed factors that have been found to influence the success of movies in extant literature. These influential forces come from critic and user ratings, the number of reviews given by both movie critics and audiences, budget, star power, and movie runtime.

Movies are an experience good, hence it is difficult for consumers to evaluate quality before actually watching the movies. Similar to other experience goods (e.g., restaurants, travel services, and games), consumers tend to rely on past opinions of other consumers, which could be either peers or critics to make purchase decisions (Nielsen, 2013). There have been many studies on the role of user reviews (i.e., user ratings and the number of user reviews; (Duan et al., 2008; Liu, 2006b) and critic reviews (i.e., ratings and number of critic reviews; Basuroy et al., 2003; Legoux et al., 2016) on success of movies. Reviews both spread awareness as well as generate buzz around the movies to attract new audiences (Deer et al., 2019). Movies that receive consumer reviews are more likely to experience an increase in demand (Dellarocas et al., 2007b; Houston et al., 2018). Then in turn new audiences will spread out reviews to their network connections, generating more demand for the movies (Deer et al., 2019; Duan et al., 2008). We controlled the effect of user and critic reviews (i.e., ratings and number of reviews) to isolate the variability of chart success driven by user and critic reviews. We used the rating scores as well as the number of reviews given on IMDb website to operationalize user and critic reviews. IMDb measures the satisfaction of users on a 10-point scale, while critics reflect through a 100-point rating system. Besides the ratings, IMDb updates the latest number of reviews a movie has received.

Next, we controlled production budgets in U.S. dollars. Movie budgets are often considered as a signal for quality and profits (Rubin et al., 2022). It is because high movie budgets mean production studios can use more advanced editing, put more visual effects, and even cast top-tier movie stars. Movies with large budgets tend to have the resources to carry out large-scale advertising, hence they can reach a larger pool of consumers to increase movie performance (Karniouchina, 2011).

In the motion picture industry, the stars are also a key indicator of chart success of movies (De Vany & Walls, 1999; Holbrook, 1999; Sochay, 1994; Basuroy et al., 2003). Particularly, when social media facilitates parasocial relationships between audiences and movie stars, audiences who are a fan of particular people in the casts tend to watch the movies for no other reasons than just to see their favourites (Calder et al., 2016). To operationalize star power, we counted the number of cast members who have at least received one award or nomination in prior years (Pastorekova, 2015).

We included movie runtime as the last control variable. It is the time between the beginning of the movie until the end including the credit scenes (IMDb, n.d.). Whether long running time might hurt chart success of theatrical releases remains questionable (Rubin et al., 2022). Yet, considering Netflix Top 10 Global is computed based on total hours viewed regardless of audiences' finishing the movies, we anticipate that movie runtime is positively related to the chart success.

**Table 1. Variable Operationalization**

| **Construct name** | **Type** | **Operationalization** | **Reference** |
|---|---|---|---|
| Chart success | Dependent | The total number of days a movie i stays on Netflix Top 10 Global. | Legoux et al. (2016) |
| "Rags to Riches" trajectory | Independent | A unidirectional trajectory that depicts a continuous emotional rise from the beginning till the end of a movie (= 1, otherwise = 0). | del Vecchio et al. (2021); Reagan et al. (2016) |
| "Tragedy" trajectory | Independent | A unidirectional trajectory that has a reverse shape of Rags to Riches trajectory. Movies following this trajectory show an ongoing emotional | del Vecchio et al. (2021); Reagan et al. (2016) |

| | | | |
|---|---|---|---|
| | | fall throughout the runtime (= 1, otherwise = 0). | |
| “Man in a Hole” trajectory | Independent | A bi-directional trajectory depicting an emotional fall followed by an emotional rise at the end (= 1, otherwise = 0). | del Vecchio et al. (2021); Reagan et al. (2016) |
| “Icarus” trajectory | Independent | A bi-directional trajectory shows an emotional rise at the beginning of the movies but then ends with an emotional fall (= 1, otherwise = 0). | del Vecchio et al. (2021); Reagan et al. (2016) |
| “Cinderella” trajectory | Independent | A tri-directional trajectory showing a rise-fall-rise pattern. Movies following this emotional trajectory tend to have happy endings (= 1, otherwise = 0). | del Vecchio et al. (2021); Reagan et al. (2016) |
| “Oedipus” trajectory | Independent | A tri-directional trajectory that is opposite to Cinderella. It follows a fall-rise-fall emotional pattern, meaning “Oedipus” movies tend to have a sad ending (= 1, otherwise = 0). | del Vecchio et al. (2021); Reagan et al. (2016) |
| Scene volatility | Independent | Indicates how rapidly movie scene alter, considering directions of change as well as the magnitude. | Berger et al. (2021) |
| User ratings | Control | A weighted average of all individual satisfaction scores IMDb users give for a movie. It is scored on a scale from 1 to 10. | Duan et al. (2008); Liu, (2006b) |
| Critic ratings | Control | The current total number of reviews on a movie posted on IMDb platform. | Basuroy et al. (2003); Legoux et al.2016 |
| Number of user reviews | Control | A weighted average of review scores given by top critics for a movie. It reflects critics' satisfaction on a scale from 0 to 100. | Duan et al. (2008); Liu, (2006b) |
| Number of critic reviews | Control | Total reviews of top critics given for a movie | Basuroy et al. (2003); Legoux et al.2016 |
| Budget | Control | Production budget measured in $ millions | Rubin et al. (2022) |

| | | | |
|---|---|---|---|
| Star power | Control | Total count of actors, actresses, and directors who have at least one award or nomination. | Pastorekova (2015) |
| Runtime | Control | The total length of the movie from the beginning till the ending credits. It is measured in minutes. | Rubin et al. (2022) |

### 3.3. Model specification

Going back to the main objective of this study, we conducted the research to uncover whether there is a relationship between emotional trajectories, scene volatility, and movie success on SVOD platforms. And further, we extended to investigate the interaction effect of those two independent variables on chart success. To address the matters, we used multivariable regression, particularly with the log-log specification. The log-log regression, which is also called the multiplicative model, holds similar properties to the additive linear regression while allowing us to examine a more flexible relationship form (Shalizi, 2015). Based on sound theories, we anticipate that our independent variables have non-linear effects on how long movies stay on top charting. Log-log regression is often the model used to reflect non-linear relationships (Kupfer et al., 2018; Paulich & Kumar, 2021). What is more important is that the statistical estimates of the log-log regression are percentage unitless numbers, so we can measure the amount of change in the dependent variable as the percentage change instead of absolute change. Therefore, we do not risk predicting an outcome value that falls outside the observed range.

Our final model is specified as the following after including both main independent variables (i.e., emotional trajectories and scene volatility) and control variables (user and critics reviews, budget, star power, and runtime). In the following Chapter 4 - Results, this will be referred to as the full model and the model which we used to testify our conjectures in Chapter 2.

$$\ln(Chart\ success_i) = \beta_0 + \beta_1 1\{T_i = \text{"Tragedy"}\}$$
$$+ \beta_2 1\{T_i = \text{"}Man\ in\ a\ Hole\text{"}\} + \beta_3 1\{T_i = \text{"Icarus"}\} + \beta_4 1\{T_i = \text{"Cinderella"}\}$$
$$+ \beta_5 1\{T_i = \text{"Oedipus"}\} + \beta_6 \ln(Scene\ Volatility_i)$$
$$+ \beta_7 1\{T_i = \text{"Tragedy"}\} \ln(Scene\ Volatility_i)$$
$$+ \beta_8 1\{T_i = \text{"Man in a Hole"}\} \ln(Scene\ Volatility_i)$$
$$+ \beta_9 1\{T_i = \text{"Icarus"}\} \ln(Scene\ Volatility_i)$$
$$+ \beta_{10} 1\{T_i = \text{"Cinderella"}\} \ln(Scene\ Volatility_i)$$

$$+ \beta_{11} 1\{T_i = \text{"Oedipus"}\} \ln(Scene\ Volatility_i) + \sum_{k=1}^{K} \gamma_k \ln(X_{ik}) + \varepsilon_i$$

Where,

i represents the unit of analysis in the model which is movie. Overall, there are 443 movie observations.

Chart success$_i$: indicates the number of days a movie i remains on Netflix Top 10 Global until it disappears.

"Tragedy", "Man in a Hole", "Icarus", "Cinderella", and "Oedipus" are dummy variables representing each emotional trajectory in movies. Each variable will take in a value of 1 if a movie observation falls into the corresponding emotional trajectory, otherwise, it is set to 0. The "Rags to Riches" trajectory is not listed in the model because it is used as the baseline.

The variable $X_{ik}$ represents the control variables, including IMDb user ratings, critic ratings, number of user reviews, number of critic reviews, budget, star powers, and runtime. Same as the scene volatility variable, we took log transformation for these control variables to obtain elasticity estimates and to deal with any skewed data.

Lastly, $\varepsilon_i$ is the random error term of the model.

## 4. Results

### 4.1. Descriptive statistics

Data were collected on nine external (or "profiling") factors reflecting six emotional trajectories for a total of 443 movie screenplays. 20% of the sample (N = 89) was under the "Man in a Hole" trajectory; this cluster also had the largest proportion. Other clusters provided an average of 16.7% to the sample, with the "Rags to Riches" trajectory contributing the smallest overall, 12.64% (N = 56). Generally, the size of all clusters did not fluctuate substantially and was scattered rather evenly, providing for a more objective and transparent perspective of the differences.

**Table 2. Summary statistics of numeric variables only**

| Variable | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Chart success | 443 | 15.9 | 12 | 7 | 105 |
| Scene volatility | 443 | 0.913 | 0.211 | 0.146 | 1.35 |
| IMDb user ratings | 443 | 6.08 | 1 | 2.6 | 8.7 |
| Number of user reviews | 443 | 403 | 690 | 2 | 6100 |

| | | | | | |
|---|---|---|---|---|---|
| IMDb critic ratings | 443 | 52.1 | 11.1 | 18 | 89 |
| Number of critic reviews | 443 | 98 | 122 | 2 | 634 |
| Star power | 443 | 15.4 | 12 | 1 | 103 |
| Budget (in million US dollars) | 443 | 36.5 | 46.4 | 5 | 250 |
| Runtime | 443 | 109 | 19.9 | 45 | 194 |

Overall, "Man in a Hole" (e.g., “The Adam Project” movie, “The Dark Knight Rises” movie, and “The Gentlemen” movie) and "Oedipus" (e.g., “Kingdom: Ashin of the North” movie, “Our Father” documentary film, and “Seoul Vibe” movie) trajectories achieved the highest chart success, averaging 17.6 (*SD* = 11.7) and 17.8 (*SD* = 13.5) days in Netflix Top 10 Global, respectively. These two also rated the highest in scene volatility, with a rather rapid change in scene at 0.9 on average. The movies in these two trajectories, conversely, had a low number of user reviews as well as the lowest star power. Among the two trajectories, movies following “Man in a Hole” emotional trajectory on average are appraised more highly than movies under the “Oedipus” one.

The "Rag to Riches" trajectory, on the other hand, had the weakest chart performance (11.9 days in Netflix Top 10 Global) but garnered the most user reviews, the greatest IMDb user rating, and relatively strong star power. For instance, “Blade Runner 2049” movie was directed by the Oscar-nominated filmmakers Denes Villeneuve and Roger Deakins, and even impressed the public with A-tier movie stars like Ryan Gosling, Harrison Ford, and Jared Leto. In spite of that, the movie disappeared from Top 10 Global after 7 days which is the lowest record among the observations. This suggested that the chart success of a movie on a specific trajectory might not be owing to certain influential forces.

Movies with "Cinderella" and "Icarus" emotional trajectories had the most critical reviews, presumably due to the relatively high star power in both, but scored poorly in IMDb critic ratings, as well as IMDb user ratings and reviews. The emotional trajectory with the strongest critic rating was "Tragedy" (i.e., movies that have monotonous emotional trajectory with unhappy ending); however, movies in this cluster also had the lowest user rating and chart performance. This might imply a discrepancy between critic ratings and the chart success of a movie on Netflix streaming platform.

**Table 3. Summary statistics by emotional trajectory**

| | **Cluster 1 Rags to Riches** <br> *N = 56* | **Cluster 2 Cinderella** <br> *N = 74* | **Cluster 3 Icarus** <br> *N = 88* | **Cluster 4 Man in a Hole** <br> *N = 89* | **Cluster 5 Oedipus** <br> *N = 62* | **Cluster 6 Tragedy** <br> *N = 74* |
|---|---|---|---|---|---|---|
| Chart success | 11.9 | 15.6 | 16.7 | 17.6 | 17.8 | 14.5 |
| Scene volatility | 0.929 | 0.886 | 0.91 | 0.935 | 0.928 | 0.893 |
| IMDb user ratings | 6.32 | 6.11 | 6.06 | 6.15 | 6.05 | 5.84 |
| Number of user reviews | 462 | 339 | 493 | 347 | 394 | 390 |
| IMDb critic ratings | 53.7 | 51.8 | 50.3 | 52.4 | 53.2 | 61.7 |
| Number of critic reviews | 108 | 101 | 108 | 82.7 | 96 | 96.1 |
| Star power | 16.8 | 15 | 16.1 | 14.5 | 14.1 | 16.1 |
| Budget (in million US dollars) | 35.6 | 41 | 41.5 | 30.5 | 37.8 | 32.7 |
| Runtime | 114 | 104 | 106 | 111 | 112 | 111 |
| Films (English) | 33 | 48 | 57 | 50 | 30 | 40 |

*Note: For each variable, we reported the average value as measure of central tendency*

### 4.2. SVOD chart success model estimation results

A multiple regression analysis was performed to determine whether different emotional trajectories, interactions between those trajectories and scene volatility, and control variables predicted the chart success of a movie. For this research, natural logarithmic transformation was implemented. This technique is an effective way to convert a highly distorted variable into a more normalized database. When analyzing variables with non-linear correlations, the likelihood of generating errors may be skewed adversely. Theoretically, it is desirable to provide the minimal error achievable while providing a prediction, while simultaneously ensuring that the model is not overfitted. Overfitting arises when there are other dependent variables in operation that the dataset lacks generality to produce an accurate assessment.

Utilizing the logarithm of one or more variables increases model fit by converting the feature distribution to a more normal bell-shaped curve. The emotional trajectory "Rags to Riches" was selected as the baseline reference in the current study.

**Table 4. Results for SVOD chart success models**

| | Dependent variable: Ln(Chart success) | | |
|---|---|---|---|
| | Emotional trajectories only (1) | Interaction between six emotional trajectories and scene volatility (2) | Control variables included (3) |
| Tragedy | 0.18 · | 0.23 · | 0.25* |
| | (0.11) | (0.11) | (0.11) |
| Man in a Hole | 0.35*** | 0.41*** | 0.41*** |
| | (0.1) | (0.11) | (0.11) |
| Icarus | 0.29** | 0.29* | 0.34** |
| | (0.1) | (0.11) | (0.11) |
| Cinderella | 0.22* | 0.22 · | 0.25* |
| | (0.11) | (0.12) | (0.11) |
| Oedipus | 0.36*** | 0.42*** | 0.41*** |
| | (0.11) | (0.12) | (0.11) |
| Ln(Scene volatility) | | -0.22 | -0.13 |
| | | (0.28) | (0.28) |
| Tragedy x Ln(Scene volatility) | | 0.29<br>(0.34) | 0.12<br>(0.33) |
| Man in a Hole x Ln(Scene volatility) | | 0.58<br>(0.38) | 0.45<br>(0.38) |
| Icarus x Ln(Scene volatility) | | 0.03<br>(0.34) | 0.02<br>(0.33) |
| Cinderella x Ln(Scene volatility) | | 0.06<br>(0.39) | 0.02<br>(0.38) |
| Oedipus x Ln(Scene volatility) | | 0.47<br>(0.36) | 0.28<br>(0.36) |
| Ln(IMDb user rating) | | | 0.01 |
| | | | (0.17) |
| Ln(Number of user reviews) | | | 0.09***<br>(0.02) |
| Ln(IMDb critic rating) | | | 0.07 |
| | | | (0.14) |
| Ln(Number of critic reviews) | | | -0.15***<br>(0.03) |
| Ln(Star power) | | | -0.03 |
| | | | (0.05) |

| | | | |
|---|---|---|---|
| Ln(Budget) | | | 0.02 |
| | | | (0.01) |
| Ln(Runtime) | | | 0.27 |
| | | | (0.16) |
| Intercept | 2.32*** | 2.29*** | 0.69 |
| | (0.08) | (0.08) | (0.88) |
| R-squared (Adjusted R-squared) | 0.0365 (0.0255) | 0.0479 (0.0236) | 0.1070 (0.0691) |

*Note: "***" - p < .001, "**" - p < .01, "*" - p < .05., "·" - p < 0.1. The emotional trajectory "Rags to Riches" is used as the base reference.*

Prior to the assessment of model fit and interpretation of significant results, we conducted some inspections on regression assumptions. If any violations are detected, we can implement remedies in the early phase to avoid producing unreliable results. According to the statistical results of studentized Breusch-Pagan's test for heteroscedasticity (Koenker, 1981) and Durbin-Waston's test autocorrelation (Durbin & Watson, 1951), we found no presence of heteroscedasticity (*Breusch-Pagan value*(18) = 22.79, $p$ = 0.2) and autocorrelation (*Durbin-Watson value* = 2.14, $p$ = 0.93) in our log-log regression model.

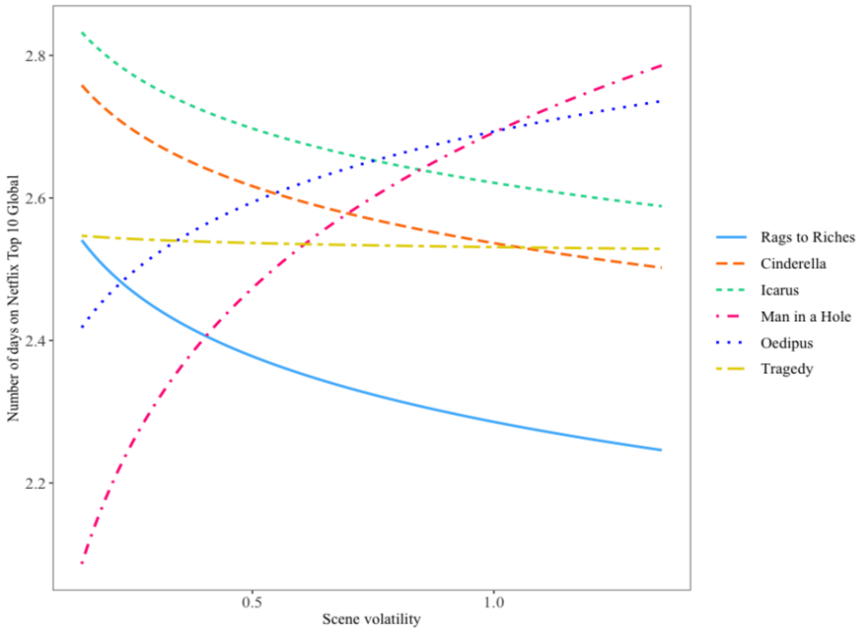
Another issue that tends to occur when building a regression model with multiple predictors is multicollinearity. Especially in our case, it would be an issue if for example the amount of variability of user reviews can be explained by other variables like emotional trajectories, scene volatility, and star power. To confirm the model is resilient to multicollinearity, we computed variance inflation factor (VIF) scores and compared them to the threshold of 10 (Belsley et al., 2005; Snee, 1983). No VIF values of our studied variables are higher than 3, hence multicollinearity is not a problem (Appendix B).

***Six emotional trajectories and SVOD chart success of movies***

In a model incorporating only the six emotional trajectories, a significant regression equation was observed for all six emotional trajectories, with "Man in a Hole" and "Oedipus" (both $p$ < .001) showing the strongest significant level. Breaking it down per trajectory, when compared to the "Rags to Riches" trajectory, movies that follow either one of the other five emotional trajectories are more likely to stay on Netflix Top 10 Global longer. Particularly, movies in "Man in a Hole" trajectory (emotional fall at first then followed by a rise in emotions at the end) tend to be on top charting for 35% longer in time than the "Rags to Riches" trajectory (an ongoing emotional rise) which stays on top 10 for an average of 10 days. This result was consistent with the study of del Vecchio et al. (2021). Surprisingly, "Oedipus" trajectory which was initially expected to be unsuccessful in terms of the number of days on Top 10 Global outperforms other trajectories. On average, movies in "Oedipus" trajectory stay on the chart for 36% longer in time than "Rags to Riches" movies. The effect magnitude of other emotional trajectories on chart success is 29% for the "Icarus" trajectory, 22% for the "Cinderella" trajectory, and 18% for the "Tragedy" trajectory.

***The synergistic effects of six emotional trajectories and scene volatility on SVOD chart success of movies***

**Figure 3: Synergistic effects of emotional trajectories and scene volatility on chart success**




The estimates in the previous sub-section have not yet considered the synergistic effects of emotional trajectories and scene volatility on chart success. By including the interaction terms, we could address whether the impact of scene volatility on chart success of movies varies across different emotional trajectories. For movies following "Man in a Hole" trajectory, we found that an increase of 1% in scene volatility can prolong time staying on Netflix Top 10 by 0.36%, but the effect diminishes as movie scenes get more volatile (Figure 3). The same goes for movies in "Oedipus" trajectory, with an increase of 0.25% in time on top charting with every 1% increase in volatility. It is worth noticing that while the effect of scene volatility on chart success of movies following “Man in a Hole” and “Oedipus” trajectories are diminishing positive, “Cinderella”, “Icarus”, and “Tragedy” movies are more likely to drop out of the Top 10 Global as scene volatility increases.

Nevertheless, the statistical tests did not support the significance of the synergistic effects of emotional trajectories and scene volatility. Scene volatility particularly was revealed to have no influence on the chart success ($b$ = 0.03, $SE$ = 0.09, $p$ = 0.765), and also did not impact the effect of different emotional trajectories on the chart success of a movie. This suggested that the success of a movie regarding chart performance would most likely be unaffected by scene volatility. Further discussion on this will be presented in the following chapter.

***Control variables***

The sign of significance, on the other hand, was recorded when control variables were included in the model. The number of IMDb user ratings and critic ratings, in particular, were proven to have a relatively significant impact on a movie's chart success. To be more specific, a 1% rise in IMDb user ratings might increase the time on Netflix Top 10 Global by 0.09%, whereas a 1% increase in critic ratings could reduce the chart success by 0.15%. Such a negative relationship between the number of critic reviews and movie success was in fact quite unanticipated to discover. This matter will be further discussed in the next point.

Meanwhile, we also found marginally positive effect of movie runtime on chart success ($b = 0.27$, $SE = 0.16$, $p = 0.1$). Given the fact that the number of days on Top 10 Global is computed based on total hours viewed, our findings further implied the longer the movies the longer they remain on top charting.

In general, the observed significant effect of the number of user ratings on chart performance was consistent with earlier findings (Deer et al., 2019; Duan et al., 2008; Liu, 2006). It has been suggested that the explanatory power or even prediction power was generated by the number of user reviews, not the user ratings (Duan et al., 2008; Liu, 2006). Indeed, while the number of user reviews spreads awareness to consumers as well as generates the buzz surrounding the movies (Deer et al., 2019), user ratings are typically consumers' opinions aggregated across a different mix of positive, neutral, and negative scores (Bai, 2011). Due to the aggregation, the information conveyed from user ratings may not be enough, hence consumers may acquire other information aside to decide which movie to watch (Li et al., 2013; Moore, 2015). That might explain why movies with a high number of user reviews are more likely to survive longer on Netflix Top 10 Global, but high user ratings do not necessarily guarantee chart success.

As previously mentioned, it was somewhat unexpected that the number of critic reviews was associated with poor performance on the Top 10 chart. We reckoned that the negative effect may be driven by two reasons. First, considering that number of user reviews was positively related to SVOD chart success, it could possibly indicate that consumers are more inclined to trust other consumers more than critics (Dellarocas, 2006). Second, it is worth noting that movies that received many reviews from critics tend to be theatrical releases that later got distributed to streaming services. And based on our collected data, the total time these movies stayed on Netflix Top 10 Global is one of the shortest records, around 7 to 14 days. This could somehow clarify the negative relationship between the number of critic reviews and SVOD chart success. For instance, the "It" horror movie, which was released in cinemas worldwide and garnered 634 critic reviews, only hit the Top 10 for 7 days. Though the study postulated certain interpretations of the findings, it is important to exercise these explanations with caution because they have not been statistically testified.

### 4.3. Robustness checks

***Robustness check 1: missing data on the control variable budget***

Problems with large amount of missing values arose when handling the budget. Half of the observations did not record the corresponding budget information. This required a thorough investigation and a suitable treatment since completely ignoring the missing budget data might result in biased estimates and incorrect hypothesis tests. We suspected that the mechanism causing a loss in budget information is completely at random (MCAR). It means there is no systematic relationship between the missing budget values and any other observed variables in the data (van Buuren, 2018). In the correlation matrix (See appendix C), it showed no sign of variable budget being missing together with other variables.

The frequently used remedies for handling MCAR are either performing analysis on complete observations only or imputing the missing by regression (van Buuren, 2018). The latter technique has been widely used in various fields (e.g., medical research, psychological research, and marketing; Saar-Tsechansky & Provost, 2007; Rassler et al., 2008). In our case, we opted for the latter approach than the former because deleting half of the 443 movie observations may make it hard to detect such significant effects of emotional trajectories and scene volatility on chart success. We substituted missing budget values with the predicted budget values generated by regressing budget on other variables in the data.

Yet, we still conducted two robust regressions to determine if the significant results of our model estimation remain. In one of the models, only completed budget observations were used as input (Appendix E), whereas the second one is close to the main model except the control variable budget (Appendix D). Compared to the full model, the results of these robust regression models were not substantially different. Similarly, we found significant effects of emotional trajectories on chart success of movies on Netflix and no effect from scene volatility. However, in the model with completed observations (Appendix E), it is noticeable that the effects of emotional trajectories were detected at a much smaller significant level ($p < .1$). It could be because after omitting the missing budget values we were left with a relatively small observations per emotional trajectory, less than the standard sample size of 30 (Appendix I).

***Robustness check 2: influential observations***

Throughout the model estimation, all 443 observations, every studied variable, and even imputed budget values were included. One might be concerned that the main results would not be comprehensive unless influential observations are isolated. Though influential observations could disproportionally alter the log-log regression estimates, it required further investigation to disentangle whether the points are indeed impactful. For that reason, we ran the full version of the log-log regression model first (See table 4, model 3), then considering fitting a robust model with unusual observations removed as a sensitivity analysis (Appendix H).

Influential observations could be classified as either of the three types, including an outlier, a leverage point, or a combination of both outlier and leverage. Outliers could be briefly identified by scanning through the Q-Q plot as they do not follow the general trend of the rest. According to the Q-Q plot (Appendix J), the two potential outliers are namely "Red Notice" movie (143rd observation) and "Blood Red Sky" movie (239th observation), which have stayed on Netflix Top 10 Global for 98 days and 105 days respectively. Apparently, our main model (See table 4, model 3) underestimated that "Red Notice" remained on top charting up to 14 days. In fact, the movie was on Netflix Top 10 for 98 days. That being said, there are still other potential outliers we might have missed; hence we deployed a more effective measure called Cook's distance to capture all possible outliers in our 443 observations.

In terms of high leverage points, we compared if any observations are above the threshold of two times the ratio of number of parameters (p) and the sample size (n) (Dalpiaz, 2021). It indicated that the observations have extreme combinations of predictor values. Looking at the "Index Plot of Ratio" (Appendix G), 10 observations were identified as high leverage points. In our case, these observations were also outliers since their records on number of days on Netflix Top 10 Global were either extremely high (i.e., 105 days) or extremely low (i.e., 7 days).

To effectively detect all potential influential observations, we calculated Cook's distance for all observations to filter out any observations that have Cook's distance values greater than 4/sample size of 443. In short, Cook's distance shows how much the predicted chart success would change if the influential points were omitted. As a result, we found 24 influential observations and obtained a new robust dataset of 419 movies (Appendix F).

The new robust regression in Appendix H demonstrated the results of our proposed model (Chapter 3) but without the influential observations. Compared to the main model estimation (See table 4, model 3), the simple effects of six emotional trajectories remained statistically significant ($p < .05$). Furthermore, even without the influential observations, there was not enough evidence to support the synergistic effects of emotional trajectories and scene volatility on chart success. As for control variables, alongside with number of user and critic reviews, we noticed that runtime turned to be significantly positively related to chart success of movies on Netflix Global ($b = 0.42$, $p < .05$). What can be concluded is that the relationship between emotional trajectories and chart success is significantly strong regardless of the influential observations.

Although the influential observations did not impact the significance of the studied relationships, the removal of those points indeed enhanced the elasticity estimates of each emotional trajectory. Interestingly, the R-squared has substantially increased from 0.107 to 0.1558 because of excluding influential observations. Without those noises, the new model (Appendix H) managed to explain nearly 15.58 percent of the variability of the movie chart success. The diagnostic plots (Appendix K) also showed a better fit.

**Table 5. Summary of key effects**

| **Hypotheses** | **Findings** |
|---|---|
| H1a: Movies with emotional trajectories resembling "Man in a Hole" and "Cinderella" shapes are positively related to SVOD chart success. | ***Accepted*** |
| H1b: Movies with emotional trajectories resembling "Rags to Riches", "Tragedy", "Icarus" and "Oedipus" shapes are negatively related to SVOD chart success. | ***Rejected*** since "Tragedy", "Icarus", and "Oedipus" were found to be positively related to chart success of movies on streaming services |
| H2: Scene volatility has a positive effect on SVOD chart success | ***Rejected*** due to the insignificant effect |
| H3a: The synergistic effect of "Man in a Hole" trajectory and scene volatility is positively related to chart success | ***Rejected*** due to the insignificant effect |
| H3b: The synergistic effect of "Cinderella" trajectory and scene volatility is positively related to chart success | ***Rejected*** since the interaction effect between scene volatility and "Cinderella" emotional |

trajectory on chart success was negative, yet insignificant.

### 4.4. Exploratory research

***The effect of scene volatility on user ratings***

Contrary to prior research, the effect of scene volatility on chart success of movies has constantly shown to be insignificant in the study. A probable explanation is that the influence of volatility is more likely to be observable on individual consumer level than institutional level. Indeed, previous research strictly manipulated volatility in movies to observe participants' watching behaviors in a lab setting (i.e., participant's continuing the content consumption, participant's post-consumption evaluation; Etkin & Mogilner, 2016; Berger et al., 2021). That was not the case in this study. The observed outcome in this study is measured on movie level. Chart success of movies, reflected through accumulated number of days on Netflix Top 10 Global, could be dependent on either observed factors (e.g., emotional trajectories in movies, number of user reviews, and number of critic reviews) or unobserved factors (e.g., studios' strategic decisions and Netflix's recommendation system). To test this speculation, we ran a replica of prior research which regressed user ratings on scene volatility because it can reflect preferences of individual consumers.

**Table 6. The effect of scene volatility on user ratings**

| | Dependent variable | User ratings |
|---|---|---|
| | Estimate | SE |
| (Scene volatility)$^2$ | 1.35 · | 0.77 |
| Scene volatility | -2.27 · | 1.25 |
| Intercept | 6.97*** | 0.5 |

*Note: "***" - $p < .001$, "**" - $p < .01$, "*" - $p < .05$., "·" - $p < 0.1$.*

In the light of this, the results revealed that the relationship between scene volatility and user ratings took on a quadratic shape better than logarithmic one. And more particularly, it is a concave upward relationship as the coefficient of the second order term is negative ($b$ = 1.35, $SE$ = 0.77, $p$ < 0.1). From the standpoint of the minimum scene volatility, we could make two interpretations on the effect of scene volatility on user ratings. For movies that are volatile less than 0.84, an increase in scene volatility is negatively associated with user ratings. On the other hand, given among movies that are already volatile beyond 0.84, boosting the scene volatility are likely to make consumers rate the movies higher. This implied that more volatile movies tend to receive favourable consumer evaluations on IMDb website.

## 5. Conclusion

Thus far, the thesis empirically investigated the hypothesized relationships between emotional trajectories, scene volatility in movie screenplays, and movie success on streaming platforms. Besides, the paper attempted to explore the synergistic effects of emotional trajectories and scene volatility to bring to light which combination of the two entertainment features is associated with good SVOD chart performance. Additional influential factors like user and critic reviews, movie budget, the power of movie casts, and movie runtime were also incorporated in the exploratory model, hence our empirical findings revealed the true effects of emotional trajectories as well as scene volatility. In the following sections, we thoroughly reviewed the contributions this study has made by addressing each area, namely empirical, theoretical, and managerial.

### 5.1. Empirical findings and discussion

Regarding the empirical findings, one of the research questions posed at the beginning is ***to what extent the six emotional trajectories are related to the SVOD chart success of movies***. An analysis of the emotional trajectories available demonstrated that the two trajectories of "Man in the Hole" and "Oedipus" received the highest rate of success concerning the number of days spent in the Netflix top 10 Global. Comparing the strongest categories with the weakest ones, it was found that movies in the "Man in a Hole" and "Oedipus" categories stayed on the chart for about 35-36% longer than the Rags to Riches trajectory. Some notorious examples belonging to these two emotional trajectories are "The Adam Project" movie and "Major Grom: Plague Doctor" movie, and "The Whole Truth" movie, with records of 56 days, 49 days, and 35 days on Netflix Top 10 Global respectively. On the other hand, the "Rags to Riches" trajectory was the weakest performing. Generally, the evidence from the study suggested that If a movie falls under any of the other five emotional trajectories other than "Rags to Riches", it is more inclined to survive on the Netflix Global Top 10 chart on average more than 10 days.

There is an important difference between our findings and del Vecchio et al. (2021). Nevertheless, to a certain extent, the effects of six emotional trajectories on movie success on streaming services are quite similar in the context of a novel study by Reagan et al. (2016). In the theatrical release context, movies keeping audiences immersed in different stages of emotional development tend to be financially successful (Green & Brock, 2000; del Vecchio et al., 2021). And not only that, but the movies also need a happy ending in order to be successful regardless there is an emotional fall in the middle of the movies (del Vecchio et al., 2021). The two emotional trajectories possessing these characteristics are “Man in a Hole” and “Cinderella”. In other words, the other emotional trajectories resembling “Rags to Riches”, “Tragedy”, “Icarus”, and “Oedipus” do not perform well because they either display monotonous emotions or have sad closure. In comparison, interestingly, when replicating the study to movies on streaming services, “Oedipus” and “Icarus” emotional trajectories were shown to hit the Top 10 Global longer than the “Cinderella” trajectory. This coincided with successful emotional trajectories found in novels (Reagan et al., 2016).

One might be concerned that prior research has evinced that when experiencing time-limited good like movies consumers prefer to see an emotional uplift at the end (Kahneman et al., 1993). Then why would the two emotional trajectories that leave audiences with an unhappy ending like “Oedipus” and “Icarus” succeed on the Top 10 chart? These rather contradictory findings may be explained by whether audiences have full control over the time of consumption (i.e., the amount of time people spend to finish watching). In a cinema, once a movie is on screen, it continues to play until the final minute of the runtime (e.g., 108-minute screening non-stop). Consumers of streaming services, on the other hand, could possibly opt-out and resume at any point of the movie as they want. This behavior may be similar to how people read a novel. When consumers are free to take much time to consume the content, consequently it helps to diffuse the emotional intensity experienced from the unhappy ending in the movie, thereby making the unhappy-ending movie more enjoyable to watch. This also implied with caution that movies following “Oedipus” and “Icarus” emotional trajectories can perform well on the SVOD chart if audiences can digest the content at their own pace.

The next research questions we aimed to address are ***to what extent scene volatility is related to chart success, and how combining different emotional trajectories with scene volatility can influence the SVOD chart success of movies***. The initial conjecture on the studied relationships was that in general scene volatility had a diminishing positive influence on chart success. More specifically, it was anticipated that the scene volatility can boost “Man in a Hole” and “Cinderella” movies to perform better on streaming platforms since the two emotional trajectories were posited to be successful trajectories in prior literature (MacInnis & Price, 1987; del Vecchio et al., 2021). Our conjectures were based on the mechanism that scene volatility increases stimulation by adding variety to the experience, hence keeping audiences engaged in the movies longer (Ratner et al., 1999; Etkin & Mogilner, 2016; Berger et al., 2021). Furthermore, rapid changes in movie scenes and scene direction (i.e., from positive scenes to negative scenes and vice versa) help improve the vividness, intensity, and concreteness of images in movies (Cutting, 2016). Thus, the vivid, intense, and concrete images transport audiences into an immersive state when watching (Murtagh et al., 2009). Surprisingly, the empirical results could not find enough statistically significant evidence to support either the simple effect or the synergistic effects. Regardless of the significance, contrary to the expectations, our estimates revealed that the effect of scene volatility on the chart success of movies with emotional trajectories resembling "Cinderella" was negative. Meanwhile, the synergistic effect between scene volatility and "Oedipus" trajectory can be beneficial to prolong days on the Top 10 chart, yet the effect would wane as movie scenes get more volatile.

From the additional exploratory analysis, it was demonstrated that scene volatility was non-linearly associated with how audiences evaluate their experiences with the movies, but it was not a factor directly driving how long movies hit the chart. One possible explanation is that audiences rate volatile movies highly to reflect their enjoyment of the movies. And narrative transportation has been suggested to be positively related to consumers' level of enjoyment (van Laer et al., 2014). Given that oscillating between positive and negative scenes may offer more stimulation as well as engender narrative transportation, an increase in scene volatility is likely to make consumers like the movies more.

However, there was no evidence in the study supporting the influence of user ratings on the SVOD chart success of movies. Interestingly, the lack of effect of user ratings on movie success aligned with that found in previous research. User ratings did not have a significant effect on the financial performance of movies, instead, it was the number of user reviews driving the success through creating awareness and buzz (Deer et al., 2019; Duan et al., 2008; Liu, 2006; Seiler et al., 2017). Consequently, we could not further conclude that scene volatility influenced the chart success of movies through user ratings.

### 5.2. Theoretical and managerial implications

The study has made several theoretical contributions. First, moving beyond the use of limited forms of text like movie trailers, movie synopsis from IMDb, or user-generated keywords (Chu & Roy, 2017; Eliashberg et al., 2007; Fowdur et al., 2009; Liu et al., 2018; Toubia et al., 2019), the study has proved the feasibility of processing full movie screenplays at a large scale (i.e., 443 movie screenplays were analyzed automatically) with the Natural Language Processing (NLP) toolkit. This has offered the benefit of extracting insightful entertainment features from movies, allowing research to finally uncover which characteristics of movies drive them to prosper on streaming platforms like Netflix.

Taking the study as an example, we proposed a reliable methodology to process, extract, and categorize movie screenplays into meaningful groups beyond the conventional genres. In particular, the two focal features studied here are six emotional trajectories and scene volatility which have been suggested to have a positive effect on the SVOD chart success and user ratings. Indeed, there are many more features in the movies that the study has not yet explored, hence hopefully this can encourage future strand of research to take advantage of movie screenplays to answer many interesting questions

Second, as far as we are aware, this is the first study that considers the interplay between six emotional trajectories and scene volatility, whereas the previous research has only investigated either emotional trajectories or scene volatility as a single independent variable (Berger et al., 2021; del Vecchio et al., 2021; Reagan et al., 2021). Although our findings did not find any statistically significant evidence supporting the synergistic effect of emotional trajectories and scene volatility on SVOD chart success of movies, it has shed a light on the directions of effects when increasing scene volatility in a movie following one of the emotional trajectories. For "Oedipus" movies, the more volatile the movie scenes get, the longer the movies are likely to hit the Top 10 chart; however, beyond a certain range, the effect will subside and hurt the performance.

Along the line, the findings provide valuable insights for the involved parties in the motion picture industry. The first managerial contribution is that screenplay writers can utilize the effects of six emotional trajectories and scene volatility to make the movies' narratives more engaging. Furthermore, working alongside data analysts could also help pre-determine how much likely the movies will hit the Top 10 when tweaking small aspects of these features. Second, to production studios and streaming service providers, this has once again bolstered the capability of data science in assessing which one among countless movie screenplays is likely to perform well on the Top 10. As the analysis has already shown the "Rags to Riches" emotional trajectory performed poorly compared to the other five categories. This might ease the burden on humans in the greenlighting process, ultimately mitigating human errors. Finally, our findings provide screenwriters and studios with specific insights to cater along their objectives. It could be utilizing the positive effect of scene volatility to produce movies that gain positive public reputation, or they could strategically produce movies following "Man in a Hole" and "Oedipus" emotional trajectories if good chart performance is the main goal.

### 5.3. Limitations and future research

While the analysis shed some light by analyzing original data that would help predict the success rate of movies on streaming platforms such as Netflix, it is not without its limitations. And there are a lot of avenues through which future research can build on the study.

The first problem, in this case, was the amount of missing data on budget. The Netflix Global Top 10 list provided little useful information, and while the information base could be substantiated by correlating it with the IMDB base, several movies still did not have much of the necessary data. It was demonstrated that the absence of budget data did not influence the estimates of the main effects of emotional trajectories and scene volatility on SVOD chart success. Nevertheless, there would seem to be a need for collecting additional from other sources, namely The Numbers and Rotten Tomatoes.

Second, despite the large number of observations used in the study (i.e., 443 English and non-English movies), it is important to be cautious of the possible selection bias in our sample. Specifically, the study solely relied on the data on Top 10 Global provided by Netflix, meaning only movies making to the Top 10 were recorded. This has induced a bias issue in choosing successful movies and neglecting the unsuccessful ones (Certo et al., 2016; Eliashberg et al., 2014; Paulich & Kumar, 2021). One possible solution for future research to tackle the selection bias is to shift the focus to investigate whether a movie has entered the Top 10 chart (i.e., binary dependent variable). By altering the objective, we could expand the sampling frame to all movies available on Netflix.

Finally, as previously mentioned in the theoretical implications, the study does not mean to imply that emotional trajectories and scene volatility are the sole features representing movies' narratives. There are, in fact, more other feature other than emotions and images in movies that are theorized to contribute to the success of movies. It is worth to mention the relative number of characters involves in the plot (Selbo, 2015) or semantic progression (i.e., how information is covered in a movie in terms of speed, volume, and circuitousness; Toubia et al., 2021). If possible, future research can incorporate these features to the nascent but blooming area.

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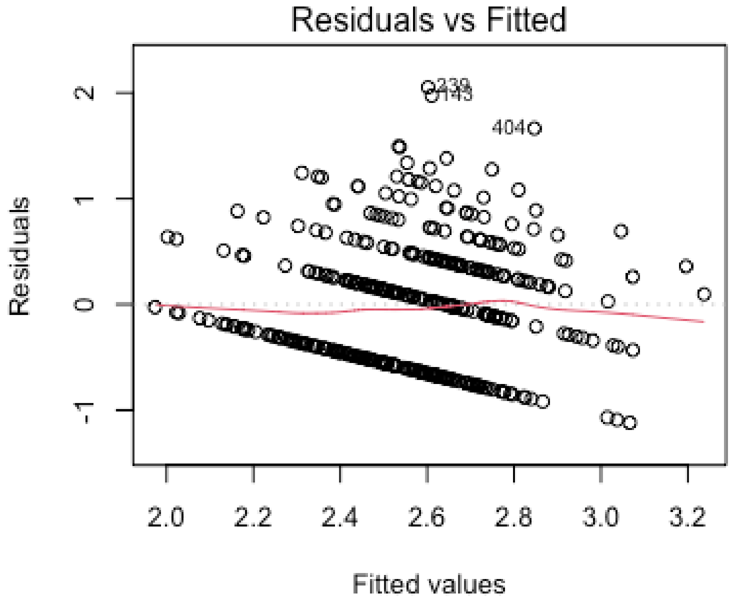
## 7. Appendices

### Appendix A: Residuals versus fitted values plot




### Appendix B: Multicollinearity table (VIF)

| Variable | VIF | Degree of freedom (df) | $VIF^{1/(2*df)}$ |
|---|---|---|---|
| Emotional trajectories | 1.12 | 5 | 1.01 |
| Scene volatility | 1.03 | 1 | 1.02 |
| User ratings | 1.33 | 1 | 1.15 |
| Number of user reviews | 2.36 | 1 | 1.54 |
| Critic ratings | 1.24 | 1 | 1.12 |
| Number of critic reviews | 2.50 | 1 | 1.58 |
| Star power | 1.86 | 1 | 1.37 |
| Budget | 1.29 | 1 | 1.14 |
| Runtime | 1.16 | 1 | 1.08 |

## Appendix C: Detect whether budget variable is missing at completely random (MCAR), missing at random (MAR), or missing not at random (MNAR)

| | Number of user reviews | Budget | Runtime | Scene volatility |
|---|---|---|---|---|
| Number of user reviews | 1 | | | |
| Budget | 0.08 | 1 | | |
| Runtime | -0.005 | 0.03 | 1 | |
| Scene volatility | -0.01 | -0.06 | -0.008 | 1 |

## Appendix D: Model estimation results without controlling for budget

| Dependent variable | Ln(Chart success) | |
|---|---|---|
| | Estimate | SE |
| Tragedy | 0.24 · | 0.11 |
| Man in a Hole | 0.41*** | 0.11 |
| Icarus | 0.34** | 0.11 |
| Cinderella | 0.26* | 0.11 |
| Oedipus | 0.42*** | 0.11 |
| Ln(Scene volatility) | -0.13 | 0.28 |
| Tragedy x Ln(Scene volatility) | 0.13 | 0.33 |
| Man in a Hole x Ln(Scene volatility) | 0.47 | 0.38 |
| Icarus x Ln(Scene volatility) | 0.0008 | 0.33 |
| Cinderella x Ln(Scene volatility) | 0.006 | 0.38 |
| Oedipus x Ln(Scene volatility) | 0.26 | 0.36 |
| Ln(IMDb user rating) | 0.008 | 0.18 |
| Ln(Number of user reviews) | 0.09*** | 0.03 |

| | | |
|---|---|---|
| Ln(IMDb critic rating) | 0.05 | 0.14 |
| Ln(Number of critic reviews) | -0.14*** | 0.03 |
| Ln(Star power) | -0.03 | 0.05 |
| Ln(Runtime) | 0.25 | 0.16 |
| Intercept | 1.00 | 0.86 |
| R-squared (Adjusted R-squared) | 0.1019 (0.0660) | |

Note: "***" - p < .001, "**" - p < .01, "*" - p < .05., "·" - p < 0.1. The emotional trajectory "Rags to Riches" is used as the base reference.

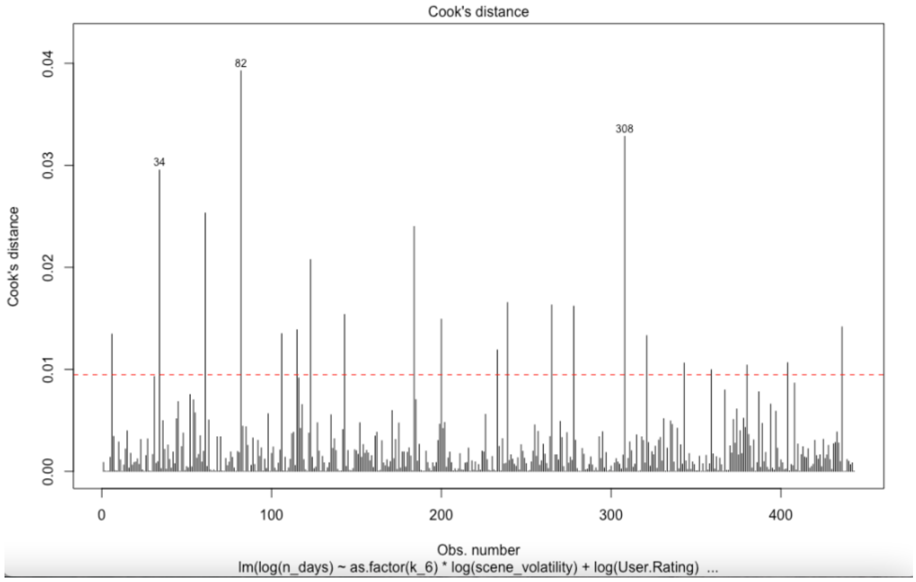
## Appendix E: Model estimation results dropping missing budget values

| | Dependent variable | Ln(Chart success) |
|---|---|---|
| | Estimate | SE |
| Tragedy | 0.33 · | 0.19 |
| Man in a Hole | 0.29 | 0.19 |
| Icarus | 0.45* | 0.19 |
| Cinderella | 0.46* | 0.2 |
| Oedipus | 0.25 | 0.2 |
| Ln(Scene volatility) | -0.03 | 0.37 |
| Tragedy x Ln(Scene volatility) | 0.23 | 0.34 |
| Man in a Hole x Ln(Scene volatility) | 0.48 | 0.39 |
| Icarus x Ln(Scene volatility) | 0.006 | 0.34 |
| Cinderella x Ln(Scene volatility) | -0.5 | 0.38 |
| Oedipus x Ln(Scene volatility) | 0.5 | 0.37 |
| Ln(IMDb user rating) | -0.12 | 0.51 |

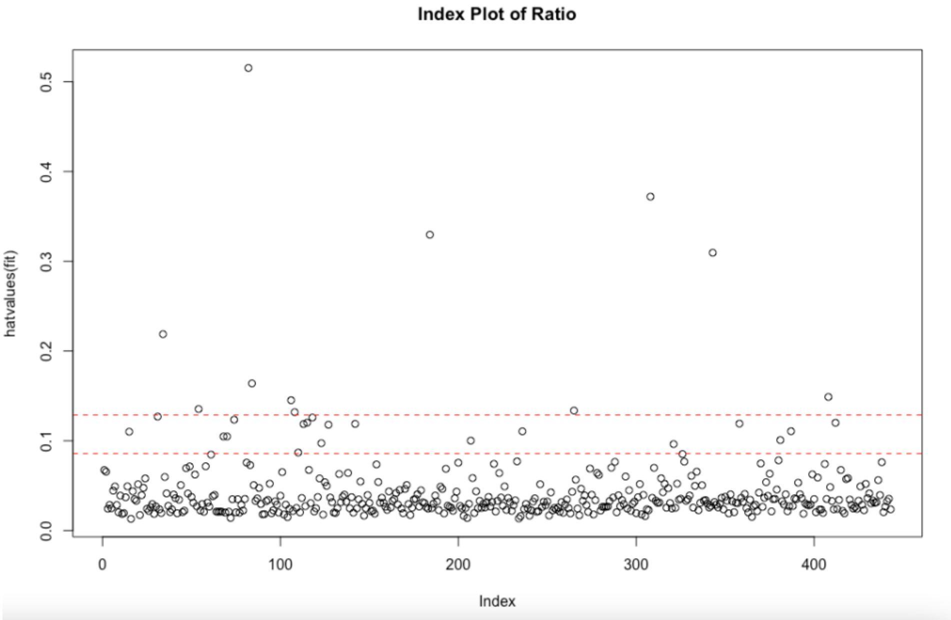
| | | |
|---|---|---|
| Ln(Number of user reviews) | 0.11 · | 0.06 |
| | | |
| Ln(IMDb critic rating) | 0.08 | 0.24 |
| Ln(Number of critic reviews) | -0.21* | 0.08 |
| | | |
| Ln(Star power) | -0.26* | 0.12 |
| Ln(Budget) | 0.14* | 0.06 |
| Ln(Runtime) | 0.2 | 0.4 |
| Intercept | -0.03 | 2.03 |
| R-squared (Adjusted R-squared) | 0.1985 (0.0962) | |

Note: "***" - p < .001, "**" - p < .01, "*" - p < .05., "·" - p < 0.1. The emotional trajectory "Rags to Riches" is used as the base reference.

## Appendix F: Cook's distance



## Appendix G: Detect high leverage points from the index plot of ratio




## Appendix H: Model estimation results without influential observations

| | Dependent variable: | Ln(Chart success) |
|---|---|---|
| | Estimate | SE |
| Tragedy | 0.27* | 0.11 |
| Man in a Hole | 0.44*** | 0.11 |
| Icarus | 0.34*** | 0.11 |
| Cinderella | 0.24* | 0.11 |
| Oedipus | 0.47*** | 0.11 |
| Ln(Scene volatility) | 0.12 | 0.4 |
| Tragedy x Ln(Scene volatility) | -0.13 | 0.46 |
| Man in a Hole x Ln(Scene volatility) | 0.19 | 0.47 |
| Icarus x Ln(Scene volatility) | -0.49 | 0.46 |
| Cinderella x Ln(Scene volatility) | -0.43 | 0.53 |
| Oedipus x Ln(Scene volatility) | 0.07 | 0.49 |

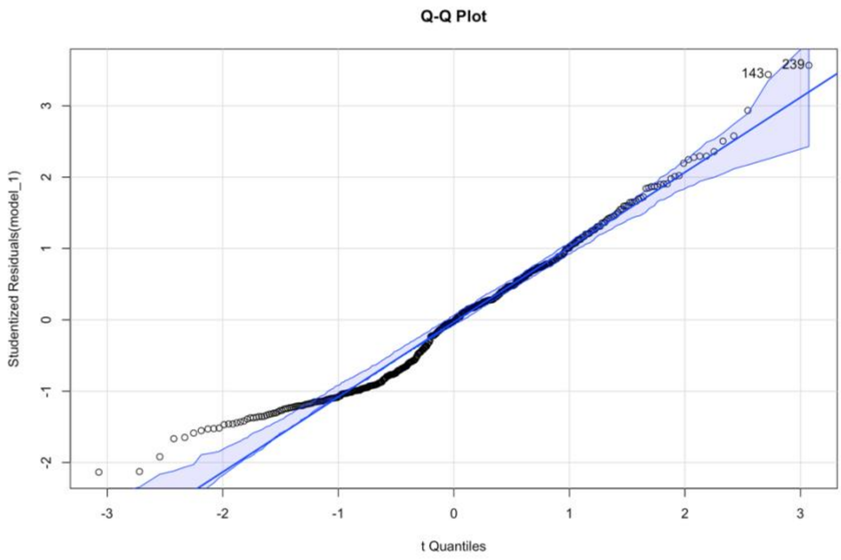
| | | |
|---|---|---|
| Ln(IMDb user rating) | 0.01 | 0.18 |
| Ln(Number of user reviews) | 0.09*** | 0.02 |
| | | |
| Ln(IMDb critic rating) | 0.1 | 0.13 |
| Ln(Number of critic reviews) | -0.17*** | 0.03 |
| | | |
| Ln(Star power) | -0.03 | 0.04 |
| Ln(Budget) | 0.02 · | 0.01 |
| Ln(Runtime) | 0.42** | 0.16 |
| Intercept | -0.18 | 0.83 |
| R-squared (Adjusted R-squared) | 0.1558 (0.1178) | |

Note: "***" - $p < .001$, "**" - $p < .01$, "*" - $p < .05$., "·" - $p < 0.1$. The emotional trajectory "Rags to Riches" is used as the base reference.

## Appendix I: Frequency statistics of six emotional trajectories after the missing budget value removal

| **Emotional trajectory** | **N** |
|---|---|
| Riches to Rags | 22 |
| Tragedy | 29 |
| Man in a Hole | 26 |
| Icarus | 32 |
| Cinderella | 29 |
| Oedipus | 22 |

## Appendix J: Detect outliers from the Q-Q plot




## Appendix K: Comparison of fitness of model without influential observations (Top) and original model will 443 observations (Bottom)