AN APPLICATION OF MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE IN THE EMOTIONAL ARC OF MOTION PICTURES TO DRIVE PRODUCT AND SERVICE INNOVATION IN THE ENTERTAINMENT INDUSTRY

by

PRASHANTH RAMAPPA,

BACHELORE OF ENGINEERING

MECHANICAL

DISSERTATION

Presented to the Swiss School of Business and Management Geneva

In Partial Fulfillment

Of the Requirements

For the Degree

DOCTOR OF BUSINESS ADMINISTRATION

SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA

MARCH 2024

AN APPLICATION OF MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE IN THE EMOTIONAL ARC OF MOTION PICTURES TO DRIVE PRODUCT AND SERVICE INNOVATION IN THE ENTERTAINMENT INDUSTRY

by

PRASHANTH RAMAPPA

APPROVED BY

Anna Provodnikova, PhD

Dissertation chair - Dr. Anna Provodnikova

RECEIVED/APPROVED BY:

Admissions Director

Dedication

I dedicate this work to my parents and my wife, who has been a pillar of strength and understanding, allowing me to fully immerse myself in this endeavor. My children have been a source of endless joy and motivation, reminding me of the importance of lifelong learning. This work is a product of your belief in me, and I hope it fills you with as much pride as the gratitude I have for you.

Acknowledgements

I want to say a big thank you to everyone who helped me finish this thesis. I am profoundly grateful to my mentor and advisor, 'Mario Sillic'. His knowledge, patience, and understanding really helped me navigate the complex parts of my research.

ABSTRACT

AN APPLICATION OF MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE IN THE EMOTIONAL ARC OF MOTION PICTURES TO DRIVE PRODUCT AND SERVICE INNOVATION IN THE ENTERTAINMENT INDUSTRY

PRASHANTH RAMAPPA

2024

Dissertation Chair: <Chair’s Name>

Co-Chair: Mario Sillic

The entertainment industry faces challenges in effectively recognizing and understanding the emotional responses of its audience. The intricacy and fundamental qualities of human emotions can often elude AI and ML models, resulting in potential misinterpretations. This study primarily focuses on developing a novel technique to analyzing the emotional journey in movies using powerful AI and ML models. The study's major goal is to create a new methodology to better understand and analyze individual movie preferences based on Emotion Intensity research, thereby improving emotional comprehension within the

entertainment industry. Our methodology presents a novel way to segment scripts and uses a lexicon-based approach, allowing the proposed work to benefit from a manually curated lexicon of terms associated with emotions. NRCLex which has been proven for providing emotion analysis has been adopted. The Lexicon categorizes text into eight basic emotions: anger, fear, anticipation, trust, surprise, sadness, joy, disgust, and two sentiments: positive and negative. We used the emotional intensity of each subscript to process it through combination of clustering methods, including K-means, Gaussian distribution, and Minibatch Kmeans. Cluster are created using custom methodology to create a pattern and then associated these patterns with emotional arcs. After analyzing various screenplays, we discovered six distinct emotional trajectories: Rags to Riches, Riches to Rags, Man in a Hole, Icarus, Cinderella, and Oedipus. We also looked at the emotional trajectory of how emotions move through a script, including positive emotional intensity (trust, anticipation, joy, surprise) and negative emotional intensity (anger, fear, sadness, and disgust). This research is essential to businesses, particularly in the entertainment industry, as it provides a prospective decision support system that could greatly enhance the scriptwriting process. By evaluating their scripts for emotional arcs, screenwriters can craft narratives that resonate more deeply with audiences, potentially leading to greater viewer engagement and satisfaction. Moreover, our findings highlight the commercial success associated with the 'Man in a Hole' emotional trajectory. This insight could influence strategic decisions in script selection, development, and production, optimizing resources towards content that has a higher likelihood of success. In turn, this could lead to improved financial performance and market competitiveness for businesses in the entertainment sector.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER I:

INTRODUCTION

1.1 Introduction

In the contemporary era of ever-changing trends in the entertainment industry, innovative technology and storytelling have become an important part. The present chapter forms an entry to the study of a pioneering research project regarding using ML and AI in influencing the development of product-and-service innovation through movie emotional arc creation. The meeting of these domains presents a great prospect to solve the vital issues in film screenplay development and guides the industry into new horizons of creative mastery.

At the helm of technological integration, we find leaders in the entertainment industry based on seamless blending of creativity and technology-driven insights to ensure ultimate success. However, as people's desire for powerful and relatable material goes on to increase, the necessity of knowing how best to craft emotional arcs becomes more apparent in movie production. This section serves as a well-rounded introduction to the study, disclosing factors that drive it – motivation, context, and relevance of emotions with technology (Del Vecchio *et al.*, 2021a)

The movie industry has now become a global force that rivets audiences and accounts for massive income worldwide. Indeed, according to PwC's projections, the global entertainment sector lost over 70% of revenues from cinemas in 2020 as they decreased by US$11.4billion in comparison with the previous year (US3. But a resilient recovery is expected, predicting an increase to US$9.1 billion in 2024 representing a -2.4

decline on average. Simultaneously, the VOD subscription industry is predicted to see significant growth with revenues reaching US$24.5 billion in 2036 due to new streaming services and rising demand among consumers especially during COVID-19 virus pandemic (Ahmed,2020; Carrillat,2018).

In 2020, the OTT platforms in its entire landscape made a big change. Now OTT services including streaming media and video on demand over the internet have changed this story-telling narrative. Platforms such as Amazon Prime, Voot, Hotstar Netflix, and Hulu allow the user access to a large collection of content enabling them to customize their viewing experience. The advent of web series that are mainly coming out from longer narratives has changed the way stories can be viewed, with a much more entertaining option than what previous formats could offer (Chu and Roy, 2017)

In such a fast-moving industry as entertainment, emphasis on productivity in the production of motion pictures becomes critical. In the light of operations management, filmmaking is an extensive process that requires multidimensional decision-making by different stakeholders. The difficulty of measuring productivity lies in the creative nature of this industry (Culkin, N., Morawetz, N. & Randle, K., 2008). While film production is typically measured in terms of revenue-to-budget ratios, these are limited by the various expenditure items involved.

The contemporary challenges in the motion picture sector are twofold: specific issues relevant to several sectors and general problems for innovative areas (Dashtipour,2021). The 4th industrial revolution is described as the everlasting process of transition to a digital economy that promises unimaginable data access, and automation, and blends AI and ML with data science. This revolution presents both opportunities and challenges since it requires a completely new way of understanding operations processes, and productivity.

Regardless of budgets and production capacity, a poor script may ruin the potential prospects of a movie. Also, due to the subjective nature of evaluation based on specialists' opinions and intuition, there arose uncertainties (Del Vecchio *et al.*, 2021a). There is a flood of scripts in the industry and deciding which type will find favor with audiences becomes an overwhelming task for producers, executives, and other decision-makers (Dholpuria, 2018).

However, the current problem in the entertainment industry is that understanding audience preferences and decision-making processes can be complex. Furthermore, analyzing unsuccessful movies suggests that the emotional journey may be a key issue affecting their performance. In this thesis, we aim to address this issue by proposing the use of machine learning (ML), artificial intelligence (AI), and data science. These technologies have the capability to process vast amounts of data and provide meaningful insights. Businesses will benefit from this research as it will streamline the script selection process, boost productivity, and assist in making informed decisions in the rapidly evolving entertainment landscape. Moreover, if emotional sentiment analysis becomes a critical part of the business model selection, it could empower viewers to shape content, transitioning decision-making power from producers to the audience. This shift could lead to the creation of content that resonates more with the audience, potentially improving movie success rates.

1.1.1. The Evolution of Machine Learning and Artificial Intelligence in Entertainment

Machine Learning (ML) and Artificial Intelligence (AI), through an interactive process have swept a revolution of change in the entertainment industry. This development marks a turning point in the creation, management, and consumption of content (Duan, 2017). Essential in comprehending the path of ML and AI in entertainment is to record their growth, consider notable points along this way and realize profound influence over various sides (Mykhailychenko, 2019; Del Vecchio *et al.*, 2021a).

- ***Early adoption and data-driven insights***

One of the markers that spotted this huge potential was the advent into an early phase in such a combination where ‘data-driven insights’ were beginning to emerge. With the advent of digital content, and as online channels multiplied, data became infinite. Stages then began adopting ML algorithms to decipher this data, with studios streamers and content providers gaining useful insights on audience preferences, viewing habits and performance of the contents (Eliashberg, 2006).

- ***Recommendation Systems*:**

One of the first fields in which it was used is recommendation systems. Today, ML algorithms were caught by platforms containing Netflix and amazon Prime to identify end-user behavior as well as predict preferences and provide recommendation of content based on individual. This did not only enhance the user interface, but also aided in enhancing viewer interactivity and content search (Hur, Kang and Cho, 2016).

- ***Content Creation and Script Analysis***

With the development of ML algorithms that enabled understanding and creation of natural language their use-case found creative writing along with analyzing texts. The industry even hinted at integrating AI to facilitate writers, producers and directors with regards to creative aspects (Chu and Roy, 2017; Del Vecchio *et al.*, 2021a).

Script Analysis: AI-powered programs began to read scripts as a device identifying narrative patterns, character development and emotional cycles. This differs from the conventional script assessments where a script would be evaluated based on its target audience. The mixing of Emotional Arc concepts with AI helped look at the storytelling components in a more delicate manner.

- ***Predicting a Box Office Hit***

As a result, the box office results became one of the most important aspects of the contemporary film industry where ML and AI algorithms were employed as predictors. These technologies were applied to analyze historical data, market trends and audience sentiments for reference points on release strategies and budget appropriations (Sharda and Delen, 2006; Ghiassi, Lio and Moon, 2015).

- ***Revenue Forecasting*:**

ML models were adopted by business specialists and managers for revenue analysis. These models were developed based on a range of characteristics such as genre, cast crew, release date and even sentiment analysis in promotional materials. This change from intuitive reasoning to empirical projections was the start of a different age in business when it came to amusement.

- ***Enhancing Viewer Experience***

The other aspect of evolution was the use of ML and AI to enhance viewers' impressions. Instead of focusing on the space-occupying content creation, these technologies started defining how audiences consumed and viewed entertainment (Jockel and Dobler, 2006; Kasunic and Kaufman, 2018a).

- ***Interactive Storytelling***:

At last, the concept of Artificial Intelligence-based interactive storytelling appeared to strike a chord with users who can engage and control their own narration. This is evident in the interactive films and series as viewers' decisions influenced storylines thus creating a personalized viewing environment.

Challenges and Ethical Considerations

Though the revolution of ML and AI evolves, ethical issues and challenges also emerge. The topics of algorithmic bias, data privacy and the ethics concerning artificial intelligence are engendered by discussion among industry leaders (Reagan *et al.*, 2016; Dashtipour *et al.*, 2021).

- ***Algorithmic Bias***:

The discovered bias transfer that had taken place in AI and ML systems from the used training data into their algorithms brought certain threats to stereotype perpetuation as well as exclusion. To achieve fair and equal representation of content, addressing algorithmic bias became the main objective.

- ***Data Privacy***:

Increase in the amount collected from the users for personalized recommendations and analytical purposes drew lots of valid criticism regarding data privacy. Striking the right balance between using data for insights and protecting user privacy became a complex industry.

Future Trajectory and Integration Challenges

This can be seen moving forward in the path of ML and AI within entertainment as involving deeper connections, higher-end solutions. Challenges remain; open algorithms, bias issues and the changing regulations in connection with artificial intelligence technologies are still among them (Kasunic and Kaufman, 2018a).

- ***Integration Challenges***:

There are challenges in integrating ML and AI tools into existing production workflows and creative processes without significant disruption. The professionals working in the industry should not only learn using new tools but also remain true to their creative nature of storytelling (Chew, 1988; Del Vecchio *et al.*, 2021a).

- ***Collaboration and Innovation***:

The propagation of ML and AI into the world of entertainment depends on a well-concerted effort between technologists, creatives plus industry players. Innovations in NLP, emotional analysis and deep learning are envisaged to develop the performance of these technologies (Dholpuria, Rana and Agrawal, 2018; Satyavan and India, 2019) Ultimately, the creation of ML and AI in entertainment is a paradigm shift for content generation processing and consuming. These technologies, which are data-driven insights and predictive analytics aimed at improving consumer experience have led to becoming an integral part of the industry's fabric. In the changing nature of entertainment, ethical issues and maximum utilization of ML and AI are essential for ensuring a healthy picture at all prospects in future.

1.1.2. The Conceptual Framework

In this connection, the introduction of ML and AI in entertainment is underpinned by a sophisticated conceptual framework that includes some important ideas principles adopted by these technologies. It serves as a basis of knowledge that practitioners, researchers and stakeholders apply to exploit ML & AI. This section aims to examine the elements and consequences of this conceptual framework (Reagan *et al.*, 2016; Chu and Roy, 2017).

1.1.3. Foundations of the Conceptual Framework

- ***Understanding Emotional Arcs:***

The focal point of the conceptual framework is emotional arcs in storytelling. As stated, (Reagan *et al.*, 2016) emotional arcs are the path of emotions that one takes through a story. This includes finding major emotional scenes, character development and sentiment trend. The emotional curves in a story are measured using ML and AI algorithms that break down these emotions to get their true value.

- ***Natural Language Processing (NLP):***

As a link between the language of human beings and ML's analytical capacities, NLP plays an essential role. The framework applies new-age NLP algorithms to decode the vagaries of scripts, reviews and fandom sentiments. This includes sentiment analysis, entity recognition and language modeling which facilitate systems to understand the mention of emotional as well as contextual aspects contained in text base.

1.1.4. Key Components of the Conceptual Framework

- ***Script Analysis and Feature Extraction:***

Once scripts are collected, ML algorithms can be used for their analysis and parsing out features that may include dialogue sentiment, character interactions or narrative structures. This entails segmenting the script down to granular level elements that can be quantified and analyzed. It provides the foundation to other stages, and since it enables system implementation details of storytelling components are caught.

- ***Emotional Trajectory Mapping:***

Due to this basis, the conceptual framework incorporates algorithms for plotting emotional directions. This requires developing visual embodiments of happiest and saddest points within a story. ML techniques including the clustering and pattern recognition are applied to identify universal emotional trajectories. They can be separated into archetypal formulas as shown in (Reagan *et al.*, 2016; Chu and Roy, 2017).

- ***Integration of User Feedback:***

The framework recognizes that audience response can increase the accuracy of emotional interpretations. Univariate ML algorithms aid in the processing of user reviews, social sentiments and viewer reactions to be used for iterative adjustments to emotional trajectory models. The system integration in real time with the provision of user feedback ensures evolutionary development as world preferences, wishes and cultural norms change.

1.1.5. Applications in Creative Decision-Making

For the process of script selection, using concepts from Emotional Arc with Natural Language Processing (NLP), Sentiment Analysis and Machine Learning is a new transformation. Instead of relying on non-empirical evaluation, these technologies offer an evidence-based remedy where scripts are evaluated. NLP helps to break down the intricate emotionality in writing and Sentiment Analysis measures readership feedback. This not only streamlines the decision-making process but also reduces risks associated with creative ambiguities. It presents a shift in paradigm from intuitive choices to decisions based on popular opinion of the viewers.

- ***Crafting Compelling Narratives through Data-Driven Insights:***

Emotional trajectories and Machine Learning in story formulation reflect a break from normal patterns of the narrative. Emotional insights that are derived by ML algorithms allow filmmakers to experiment with storylines. This approach helps to ensure creativity as well as enables storytelling and the satisfaction of some affective needs in a specified target group. It creates a sense of movement and greater audience investment in narrative construction.

- ***Fine-Tuning Emotional Resonance for Impact:***

The study predicts sentiment analysis and emotional arc as concepts to realigning emotions harmony in the plot. The program gives film directors the technology to tactically alter emotional cues. With this, the analysis proposes that producers can meet special audience sensitivity and improve in general cinematographic impression. Emotional calibration precision increases the level of artifice in creative decision-making, articulating story lines which deeply resonate with viewers.

- ***Mitigating Subjectivity through Quantitative Evaluation:***

The study introduces Machine Learning algorithms to reduce bias while assessing the creative aspects. Rather, the analysis highlights that this move towards quantitative assessment adds an objective aspect to decision-making. This non-subjective rational intuition nurtures a more objective and calculated decision making. The algorithms offer an objective evaluation of emotional arcs, providing data-driven insights that complement the subjectivity and human nature of creative decisions.

- ***Personalized Audience Engagement:***

The study argues that the Emotional Arc concepts and Machine Learning can be applied in user engagement beyond creative content. Through the application of emotional nuances and preferences, this analysis shows that such technologies can customize cinematic experience for an individual. This highly individualistic form of marketing represents a shift away from the standardized model, establishing stronger ties between audiences and material.

1.1.6. Ethical Considerations and Continuous Improvement

- ***Ethical Considerations in Implementing AI and ML:***

However, this merger of AI and ML into the creative decision-making process leads to several ethical dilemmas that require consideration. These ethical rules that the study portrays can help one to avoid these traps. An important element is ethical data usage, where audience sentiments are demonstrated with adequate means. Also, key elements are the algorithms' visibility and personal data protection. Notably, the study highlights how ethical frameworks should be applied to prevent unintended outcomes and respect creative processes.

- ***Ensuring Fair Representation and Diversity:***

Another significant ethical issue is bias that may be included in the algorithms. The analysis highlights the importance of removing bias to ensure fair representation and diversity in creative decision making. Disparities in sentiment analysis or emotional arc identification could unwittingly enhance stereotypes and nip some stories into oblivion. Therefore, constant development of algorithmic fairness is crucial. This encompasses regular auditing, updates, and inclusivity. The studies suggest ethical implementation approaches, which consider opposing arguments and minimize bias in AI & ML usage.

- ***User Consent and Privacy Protection:***

People's participation and privacy issues are ethical considerations for the use of AI and ML. The analysis draws attention to the concept of informed consent from users, whose information is used for sentiment analyzing in order emotion arc recognition. It emphasizes the need for transparency in data use and robust privacy protection mechanisms. It needs to be continuous improvement in tandem as technology changes so should the ethics move along. The study predicts an ethical framework that should be built on the grounds of user consent and privacy as a trust foundation between creators, platforms and audiences.

- ***Balancing Creative Autonomy and Algorithmic Influence:***

The emergence of AI and ML in creative decision-making requires a delicate balance between creativity and shallowness to which the research contributes an insight into ethical issues like advantages that are associated with algorithmic insights while maintaining directors' original vision. For achieving this balance, it is important to determine as clear guidelines the boundaries of algorithmic impact and man's creativity. In this setting, the process of continuous improvement is an iterative loop between algorithm development and creator feedback. The study shows a framework using AI and ML as an improvement rather than a replacement of creators.

- ***Feedback Mechanisms for Continuous Improvement:***

Ethical issues must also include mechanisms for feedback incorporated under AI and ML utilization. In this analysis, continuous enhancement requires technical changes alongside user or creator responses as well. They must build in open feedback loops therefore they are always improved. It involves acting on issues, correcting algorithmic biases and further improving models with real world practice. The proposed research, thus, is an iterative process that addresses the issues pertaining to ethics under consideration of what creators and viewers need.

1.1.7. Rationale for the Research

Investigating the applications of ML and AI in emotional curve films emerges at a junction between welding technological innovations as well as structural industry aggravation. This chapter illuminates the varying motives that drive on this need for such a research project.

- ***Navigating Challenges in Film Production:***

The main problems encountered with the film production process include complex decision making between producers, directors, and writers. As a rule, the process of choosing scripts is based mainly on subjective measurement and industry experience. The traditional approach to evaluate scripts includes several laborious steps that are not always impartial and therefore allow the prejudices in decisions. ML/AI technologies which make it possible to inject data into creative decisions can simplify and expedite the decision-making process.

- ***Optimizing Productivity and Resource Allocation:***

Filmmaking is expensive because it requires a great amount of capital, labor and creativity. Since most revenue versus budget ratios is done with current productivity metrics, they tend to be detailed and accurate in describing the details of creative activities. In general, data-based analyses outperform conventional productivity formulas by offering ML and AI pathways that improve resource allocation. These technologies assist by identifying preferred emotional arcs and script features that result in increased efficiency of resource utilization, reducing the possibility for over expenditure.

- ***Addressing the Subjectivity of Script Evaluation:***

These are scripts, which is one of the main aspects in filmmaking that could be subjectively evaluated as it involves professional evaluation. Built-in subjectivity and partiality with respect to the selection of scripts might distance us from unique stories that can be told no other way. Script evaluation can be done via sentiment analysis and pattern recognition, which have objective perspectives of ML and AI. With their help, they can complement human judgment through the discovery of emotional arcs and identification patterns which resonate with viewers.

- ***Harnessing Emotional Arcs for Innovation:***

Emotional arches are an essential ingredient in storytelling, contributing to the audience's engagement and satisfaction. The abilities of traditional forms in terms of understanding and harnessing emotional arcs are very limited, as they seldom possess a systematic and data-driven approach. The goal achieved by combining ML and AI is new horizons for emotional arc analysis. This involves finding trends across effective emotional trajectories, discovering relationships between the arc of emotions and people's box office popularity as well elaborating novel approaches to storytelling in line with audience preferences.

- ***Building on Existing Research Foundations***

The choice of a foundation paper, the "Improving productivity in Hollywood with data science-Using emotional arcs of movies to drive product and service innovation in entertainment industries" by (Del Vecchio *et al.*, 2021a), is used as an impetus for this study. The preparation for understanding emotional arcs and their effect has been made by previous research, (Reagan *et al.*, 2016; Chu and Roy, 2017). Proceeding from the premises, this research seeks to advance knowledge, understanding methodologies and using ML/AI in the entertainment field.

- ***Meeting Industry Demands for Innovation:***

The current entertainment industry is characterized by swift reinvention, notably through the emergence of streaming platforms such as Netflix or changing customer patterns and a digital-first culture. For it to stay competitive and relevant, the sector must make room for innovation. ML and AI offer unexplored space innovation within film production. The research seeks to promote the development of storytelling, production processes and audience experiences by conforming to industry requirements and taking advantage of technological advancements.

1.1.8. Scope and Limitations

- ***Emotional Arc Analysis***

This work focuses on finding emotional arcs in feature movies. Using the ML and AI approaches, these emotional arches that are common in films will be empirically analyzed to determine their impacts on audience response as well as implications for B/O.

- ***Script Evaluation and Enhancement:***

The importance of the most highlighted aspects is classified as follows:

  - ***Innovation in Service and Product:***

A significant aspect of the study should address what effects merging emotional arcs, NLP and AI can have on innovation in this field. This refers to the adoption of new approaches in producing content, story-telling and interaction with audiences resulting in service innovation and product development (Chu and Roy, 2017).

- ***Industry Relevance:***

The contemporary reality of the entertainment industry serves as a framework for the research that recognizes role ML and AI could play in addressing current problems. Instrumental applications and practices also fall within its domain that could directly benefit industry practitioners, further enhancing the synergistic relationship between new technologies and creative outputs (Del Vecchio *et al.*, 2021a)

Limitations of the Research:

- ***Complexity of Emotional Expression:***

Emotions are complex and subjective states which may not be captured fully even through ML/ AI tools that aim to analyze them. The study recognizes the unavoidable complexity of feelings and attempts to offer sophisticated analysis despite the technological constraints.

- ***Data Availability and Quality:***

The success of ML and AI models is largely based on data accessibility and quality. Quantity or diversity of the available data may limit their findings' generalizability. The project seeks to address this limitation through effective data collection methods and recognizing the biases in datasets (Ghiassi, Lio and Moon, 2015).

- ***Interpretation of Creative Elements***

Accordingly, creativity in the filmmaking process is a subjective and human focused practice that goes beyond mere quantitative analysis. Though the study aims to improve decision making powered by data-driven insights, it recognizes that some elements of creativity cannot be captured fully; rather they are subjective.

- ***Technological Advancements***

It is a rapidly developing field in the world of ML and AI. The investigation is carried out against the background of existing technologies and even though it relies on contemporary techniques, the study might not represent new developments. The study attempts to provide insights grounded in the contemporary technological setting (Vogel, 2015).

- ***Generalizability to Other Industries:***

Although the emphasis is on the entertainment sector, generalizability of findings to other industries might be weakened. However, the specificities of emotional arcs in film creation may not transfer directly to industries with unique features. This research is also highly transparent about the industry-specific nature of its findings (Ghiassi, Lio and Moon, 2015).

The research is focused and provides a complete picture of emotional arcs, script evaluation as well as innovation while looking at the amusement industry. While doing so, the study also acknowledges the intrinsic limitations of emotions' complexity, data scarcity constraints subjective nature of creativity emerging technologies and industry specificities. Through defining its boundaries and restrictions, the research outlines an approach to investigation which both strives for ambition while equally recognizing complexity of topics and methodologies – one that seeks significant contributions.

1.2 Research Problem

The motion picture realm, however complex the film production process may be. At the heart of all creative complexities and artistic choices, there are major industry issues that affect productivity, decision-making as well as determining motion picture success. Realizing the relevance for a systemic approach to these challenges, the research problem is elaborated (Del Vecchio *et al.*, 2018, 2021a).

1.2.1. Productivity Impediments:

- ***Complexity of Film Production:***

Movie production is a complex process with many participants, decision-making points, and complicated operations. This complexity results from a combined effort among specialists who include directors, producers, writers and actors to realize the creative idea. Complexity itself becomes a huge bottleneck to productivity, because coordination and decision-making have the subjective elements that are almost impossible or hardy quantifiable (Dholpuria, Rana and Agrawal, 2018).

- ***Difficulty in Productivity Measurement:***

However, traditional standards for measuring productivity in the film industry have become a challenge due to imaging that features imagination differently from other industries. On the other hand, unlike manufacturing industries where output per time unit can easily be computed, productivity figures are derived from creative processes. This section talks about failings of contemporary productivity measures supporting the need for new methods considering artistic and personal aspects in making movies.

- ***Impact of the Digital Economy:***

In this respect, the shift of most major world economies towards a digital economy has consequences in terms of opportunities and threats faced by the motion picture industry. Digital technologies connected people to an ocean of information on choice and fashion design. However, the control of this digital landscape gives rise to issues related to data governance and protection as well as ethical use of technology. It is essential for a company to understand and control these challenges to take advantage of the benefits offered by the digital era.

- ***Automation and Reskilling Challenges:***

The emergence of AI and ML facilitates automation scenarios capable, for instance, but it poses the question of retraining the workforce.

1.2.2. Script Selection Dilemmas

The script choice of scripts is fundamental for a successful result when making movies, or failure altogether. On the contrary, this decision-making procedure is left to subjectivity through expert judgment and intuition. The study problem is connected to the evaluation of script quality especially in defining objective criteria and tools for efficient decision making (Kasunic and Kaufman, 2018a) . It asks how Machine Learning (ML), and Artificial Intelligence techniques can be employed to improve the process of choosing a script, thereby reducing risk that sales at the box office could fall short.

1.2.3. 1Integration of ML and AI Technologies

At the intersection of Art and Technology, film is being revolutionized by the Fourth Industrial Revolution (Eliashberg, Weinberg and Hui, 2015). This section of discussion concentrates on the union between Machine Learning (ML) and Artificial Intelligence technologies which possess a special ability to redefine film production due to its capability for overcoming hurdles within entertainment.

- ***The Fourth Industrial Revolution in Filmmaking:***

The convergence of digital physical and biological technologies which is part of the Fourth Industrial Revolution remains to change the way industry operates globally. The use of data science, ML and AI is interpreted as the revolution in filmmaking. The application of this paradigm shift to help us understand the opportunities and obstacles that we face due to inheriting these advanced technologies.

- ***Specific Impediments in Filmmaking:***

The problems that are peculiar to the film industry and how they could be addressed through ML and AI as their own catalysts is another aspect of this research problem. These problems include simplified psychologist of creative process, complexity, and accuracy in the emotion evaluation by talking pictures. It is important because in developing the discussion around these issues, this study offers a guide to real solutions through ML and AI (Vogel, 2015).

- ***Opportunities for Enhancing Productivity:***

To begin with, the introduction of ML and AI technologies creates new opportunities for increasing productivity in film production. Transformative resources involve the automated performance tasks, data hard about audiences' preferences and anticipatory analytics that will ensure an effective opening box office. This section describes how these technologies allow the standardization of their operations which ensures a fair distribution of resources and finally leads to better efficiency in motion picture productions.

- ***Refining Script Selection through AI:***

In the field of script selection, ML and AI can bring about a profound change. In this section, the discussion is centered on features of these technologies to analyze mass data scripts, detect patterns for success and predict chances of a script's success. The avoidance of such cases as flops at the box office is also facilitated by application of AI-driven scripts selection and this has a positive effect on economies of film industries.

- ***Emotion Analysis and Storytelling Enhancement:***

One interesting observation that is made within the course of ML and AI use for emotion analysis as well as storytelling. These technologies offer an unparalleled level of visibility into emotional arcs, sentiment analysis and viewer engagement scales. Through the emotional complexity that stories possess, film makers can understand how to produce more meaningful content for their viewers and create a good storytelling or cinematic experience.

- ***Driving Innovation in the Entertainment Sector:***

Besides productivity enhancement, the study also focuses on how ML and AI combinations can foster creativity in a wider entertainment industry. These technologies are set to revolutionize the future of entertainment with interactive storytelling and personalized content suggestions.

1.2.4. Emotional Arc Analysis Challenges

The expressiveness is evident in the world of storytelling and serves as a pivot for characterization, plotting or interactivity. Although this influential factor complicates manufacturing, it requires sophisticated tools and methods for analysis. This paragraph describes the complicated problems of emotional arc analysis and emphasizes that computational narratology tools, including natural language processing methods play an important part in revealing emotions into cinematographic stories (Del Vecchio *et al.*, 2018).

- ***The Significance of Emotional Arcs in Storytelling:***

In relation to the challenges, it is important to note emotional arcs that encompass character and story development leading audiences' emotions (one of many things they help in determining a film). To deconstruct these arches, filmmakers need to comprehend universal stories that evoke powerful emotions.

- ***Complexities in Emotional Arc Analysis:***

The research problem centers on the difficult issues of emotional arc analysis. Challenges emanate from the subjectivity of emotions, the plurality of narrative frameworks and complexity associated with cultural dynamics in diverse contextual locations The old techniques shortchange richness and nuances of emotional arcs, hence a need for paradigm shift to computational methods (Kim, Hong and Kang, 2015).

- ***Role of Computational Narratology:***

It is in this way that computational narratology stands out as a leading character in dealing with emotional arc analysis problems. This part further describes how computational narratology, a cross-disciplinary field of intersection between narrative and computer science, provides approaches to computationally model and analyze the structures of stories. Through such algorithms and computational models, it allows for an objective analysis of emotional arcs to be done in a systematic manner.

- ***NLP Techniques for Unraveling Emotional Content:***

About emotional arcs, narrative complexity is difficult to analyze using language skills. NLP algorithms are useful in interpreting the emotions that have been encoded within movie scripts. Whether it is sentiment analysis or emotion recognition, NLP serves as a powerful toolkit for pulling out and quantifying the emotional dimensions by filmmakers.

- ***Interdisciplinary Collaborations for Robust Analysis:***

The process of emotional arc analysis is fraught with some difficulties that can be addressed only through the collaboration between producers, data scientists and linguistic experts. The interdisciplinary nature of this endeavor is emphasized, reflecting the synergy between creative vision and computational approaches. Successful collaborations offer an integrated approach that incorporates artistic sensitivity and analytical accuracy (Kim, Kang and Jeong, 2018a).

- ***Technological Solutions for Emotional Arc Challenges:***

The aim of the suggested research problem is to analyze new technological solutions that have potential for overcoming challenges to emotional arc analysis. The technologies that have emerged to meet filmmaking in terms of unraveling complexities include machine learning algorithms that can detect emotional patterns and the latest sentiment analysis tools.

1.2.5. Industry Transition and Digital Economy

The need to change industries such as entertainment into a global digital economy has also arisen. This transition provides a context for the challenges it presents with an emphasis on abundance of data opportunities. It asks how the film industry can use tremendous amounts of data while balancing automation, machine learning and AI (Sharda and Delen, 2006) . The attention is on determining the industry's preparedness for Revolution 4.0 and the impacts of productivity improvement.

The problem with research is a synthesis of the challenges inherent in film production that include productivity measures, script choice mechanisms involving ML and AI technologies as well nuances for emotional arc analysis which was tested by an industry resolving to digital economy. Having outlined these weaknesses, the research lays the ground for focused studies aimed at finding applicable solutions that would reflect an emerging entertainment landscape.

1.3 Purpose of the Research

- **Unveiling the Motivation and Direction**:

The objectives of this study are highly multifarious primarily due to a strong foundational desire in understanding the intricacies involved with entertainment development, specifically within the motion picture segment. It sets out to tackle crucial disparities, reinvent old practices and provide groundbreaking insights that would otherwise revolutionize the industry.

1.3.1. Unpacking the Objectives

Unpacking the purpose of this study requires rigorous analysis to reveal its underlying goals and ambitions in essence, this part attempts to deconstruct the complicated nature of research objectives by highlighting various aspects that cumulatively contribute towards the overall goal in improving the emotional arc movies with employ NLP AI sentimental-analysis ML.

1.3.1.1. Advancing Emotional Arc Concepts:

The first goal is to develop an emotional arc in the filmmaking. This entails taking a more in-depth look at the philosophical premises of emotional arches, their relevance to storytelling and how they affect viewer reactions. Decoding this objective involves an unpacking of the sub-layers that exist in emotional storytelling as well as clarifying how arcs serve motion pictures' narrative structure.

1.3.1.2. Harnessing Natural Language Processing

The central focus of research is to devise a method that will enable the decryption possibilities offered by NLP techniques for film screenplays. This objective is broken down by a detailed analysis of NLP techniques, algorithms and methodologies. It aims at unwinding how NLP can be used in emotional content extraction and analysis through textual material such as movie scripts with an attempt to bridge between linguistic manifestations and computational analyses, hence developing a better understanding of affective storytelling.

1.3.1.3. Infusing Artificial Intelligence for Intelligent Decision-Making

The aim of the study is to use AI as a means by which decision making in this sector can be improved. This goal needs to be disaggregated by providing a detailed analysis of the AI applications, algorithms and models. It seeks to clarify how AI can be utilized for the process of decision-making by producers, directors and writers. This objective is formulated from the premise that AI can act as a catalyst for reasoning and decision-making based on data during critical stages such as script choice and pre-production.

1.3.1.4. Unveiling the Potential of Sentiment Analysis:

The research objectives include sentiment analysis, which is an integral part of the study. This feature necessitates unwrapping, which is a more complex process of conducting an analysis on the procedures and approaches utilized in sentiment analysis. The aim is to discover how sentiment can be analyzed, therefore determining the viewers' reactions, preferences and emotional responses towards cinematographic content. This goal is closely linked to the development of filmmakers' emotional intelligence in terms of knowing how various elements that tell a story led to changes in emotion.

1.3.1.5. Machine Learning for Predictive Insights

Regarding research objectives, ML serves as a vital enabler in terms of predictive insights. Decomposing this goal entails identifying the ML algorithms, models, and frameworks mechanisms. The goal is to demonstrate how it can be used in predicting the outcome of a movie by plotting its emotional curve through NLP and sentiment analysis. This goal is aimed to equip industry stakeholders with prediction skills that inform strategic decision making and resource allocation.

1.3.2. Bridging Research and Practice

This study tries to close the gap between theory and practice. This chapter seeks to explore the complicated links between theoretical conclusions and their practical importance, as well as define instruments for establishing a win-win relationship.

1.3.2.1. The Nexus of Theory and Industry Realities

Basically, this goal is the essence of a wish to establish harmony between theoretical models and practical reality in entertainment (Del Vecchio *et al.*, 2021a). This objective is further explained by an in-depth analysis of the functional connection between theoretical frameworks created through emotional arcs, NLP, sentiment analysis and machine learning with everyday practices that are encountered within filmmaking process. It explores the symbiosis between academia and business to ensure that theoretical developments do not remain confined in academic discussion but permeate into film production.

1.3.2.2. Practical Implications for Filmmakers

The practical implications for filmmakers must be understood to close the gap between research and practice (Suresh, Sinha and Sabyasachi Prusty, 2020). Unpacking this part would involve describing how knowledge from the emotional arc analysis, NLP, sentiment analyses and machine learning can be turned into actionable strategies that might inform decisions of people involved in either creative or decision-making processes related to film production. It shows the essence of what film producers can achieve with some research conclusions to develop their skills, select scripts wisely and strengthen an emotional attachment to such productions.

1.3.2.3. Integration of Research Findings in Production Workflows

A vital aspect of translating research into practice is the smooth embedding or infusion of findings It is necessary to unpack this objective to deconstruct the methodologies and frameworks developed with the implementation of such approaches as emotional arc analysis or related technologies into the film production line (Del Vecchio *et al.*, 2021a). It delves into the integration of findings from AI, NLP, and sentiment analysis on scripts as part and parcel production process right at pre-production stages to content creation.

1.3.2.4. Empowering Industry Stakeholders:

Fundamentally, bridging research and practice is all about equipping stakeholders in the industry with actionable findings (Satyavan and India, 2019). Deconstructing this aim entails outlining the methods used to communicate researchers' results in understandable and usable terms. It investigates how the research output turns into a practical toolkit for producers, directors, and writers. This emancipation goes beyond intellectual understanding as the stakeholders are equipped with skills to implement AI-enabled decision making, use sentiment analysis for audience engagement and harness emotional arcs to enrich film watching.

1.3.2.5. Fostering a Culture of Innovation:

This objective at narrowing the research to practice gap is beyond immediate applications but focuses on establishing an innovative trend in entertainment industry (Ng, I.C, 2014). Now, we unpack this element of the paper by analyzing how it contributes to a paradigm shift and provides industry professionals with an incentive toward embracing technological innovations. It analyzes the approaches used to establish a mindset in which research findings are not treated as abstract from practical realities but motors of transformative innovation.

1.3.3. Contextualizing the Purpose:

Contextualization is crucial in determining the application of any research endeavor. The objective of this study is to place the identified problems within a wider context of the entertainment industry. Through defining a detailed picture of the current state and future direction of this industry, the research aims at individualization its findings that allow meeting such specific needs as well as demands (Del Vecchio et al., 2021a).

1.3.4. Addressing Industry Challenges:

Although the entertainment industry is lucrative and attractive, it faces several issues. These challenges are deeply situated in the purpose of this research—to tackle them head-on. From issues of productivity and script selection to concrete solutions, the study aims at providing stakeholders in this field with frameworks which will allow them to navigate uncertainties hence improve quality of motion pictures.

1.3.5. The Research as a Foundation:

This is not a single study; it aims to become the basis for further developments. Through the inspiration of a work contributing to knowledge about emotional arcs, machine learning, and artificial intelligence in filmmaking, this research purpose entails creating an ever-growing field. It is foundational for future studies, innovations, and industry revolutions.

The nature and goal of this research can also be linked with the search for innovation, practicality, and industrial robustness (Kasunic and Kaufman, 2018a). It imagines a world where emotional storytelling and technological innovations marry to not only enrich cinematic viewing but also lead the entertainment industry into uncharted territories of creativity.

1.4 Significance of the Study

In this research, the pillar of significance is the empowerment of filmmakers and industry professionals. Through its smooth incorporation of Machine Learning (ML) and Artificial Intelligence (AI), the study seeks to transform decision-making, creative ingenuity, and navigating the complex maize maze that is the entertainment landscape. This section explains the layered significance not only because it is important but also how this empowerment will manifest itself through research results (Prasetyo, Eko Prasetyo and Zainul Dzaki, 2020).

1.4.1. Empowering Filmmakers Through Data-Driven Decision-Making

Intuition and industry knowledge have always played a significant role in decision making for filmmakers, especially regarding script selection and construction of emotional arcs (Vogel, 2015). However, the value of this study is its paradigm shift towards being data driven in decision making. Using ML algorithms and AI models, filmmakers will have quantitative data to know which script has potential, how emotionally people can connect with a story or character that are on screen as well who would be most interested in watching this movie. In its methodologies and findings, the research provides a concrete structure for introducing data analytics into decision making enabling filmmakers to make informed decisions grounded in computational analysis.

1.4.2. Utilizing Predictive Analytics for Script Selection

The process of empowering filmmakers starts with the redefinition of script selection. This research uses predictive analytics for evaluating script potential, forecasting how a movie would do based on different parameters. ML algorithms leverage historical data, industry trends and audience preferences to help filmmakers predict their script performance. This prognostic approach not only eliminates part of the uncertainties related to choosing a script, but also expands the space for different kinds of exposed story (Zhou, Zhang and Yi, 2019a).

1.4.3. Enhancing Creative Capabilities Through Emotional Arc Analysis

The creative aspect of filmmaking is intrinsically linked to the emotional response that a plot elicits. Emotional arcs are key components of storytelling that often require intuition and experience to construct. In this way, the study offers filmmakers new tools for emotional arc analysis. Using NLP and computational narratology, the research provides a deeper analysis of story emotionality. These insights may be utilized by filmmakers to improve and increase the emotional intensity of their stories, thereby creating a greater connection with audiences (Suresh, Sinha and Sabyasachi Prusty, 2020).

1.4.4. Navigating Productivity Impediments with AI Solutions

Film production is complex, and resource-intensive too with many productivity constraints that impede efficiency. This study aims to address these issues by evaluating

AI tools that can make the process easier. From the pre-production period till post-production, AI technologies can help in the efficient utilization of resources and automate simple tasks to ensure maximum results. By its results, the study provides practical solutions to AI integration into film production and issues with productivity for professionals in this sector.

1.4.5. Implementing User-Focused AI Tools for Audience Engagement

Besides the creative process, AI is highlighted in terms of enhancing audience attractiveness. ML algorithms are employed in the determination of viewer preferences, feedback, and sentiments to understand audience expectations. These datasets can be used by filmmakers and other industry professionals to create more targeted content, marketing schemes as well as distribution channels with better customer engagement. User-oriented AI tool adoption is an important component in the empowerment of filmmakers to create content that resonates with their target audience.

1.4.6. Interactive Workshops and Training Programs

For this empowerment to be real, the study proposes interactive workshops and training programs. Celebrities as well as representatives of the film industry will have a chance to interact with new ML and AI tools in an immersive training setting. These workshops, based on the methods and findings of this research will provide practical training in which its users – industry practitioners can easily integrate these technologies into their workflow (Nader *et al.*, 2022).

1.4.7. Collaboration with Industry Stakeholders

Empowering filmmakers goes beyond research data. Collaborative work with the stakeholders of industries such as production houses, film institutes and technology developers are also vital. The research conceptualizes collaborations that will promote the adoption of ML and AI tools by companies. The research in terms of establishing a collaborative ecosystem that would ensure the sustaining framework for continuous empowerment and innovation (Del Vecchio *et al.*, 2021a).

1.4.8. Enhancing Productivity and Cost Efficiency

The main findings of this study are productivity and cost effectiveness in film production. Through the utilization of ML and AI technologies, filmmakers can simplify numerous aspects in production including script selection as well as post-production. The results of the study allow for improving resource allocation, reducing wastage, and therefore enhancing efficiency along film value chains.

1.4.9. Revolutionizing Script Selection

Filmmaking starts with script selection, which is the cornerstone of all other elements related to film production and fate. The introduction of ML and AI into script selection is not just evolution; it marks a revolutionary paradigm shift. In this section, the transformative capability of data-driven script selection is disclosed and discussed in detail regarding its implications for film industry (Suresh, Sinha and Sabyasachi Prusty, 2020; Del Vecchio *et al.*, 2021a).

1.4.10. Traditional Challenges in Script Selection

The process of script selection, which has traditionally been considered a subjective and intuitional one for many years is always riddled with underlying weaknesses. Screenwriters, based primarily on introspection and industry-specific trends typically make lethal script decisions which do not appeal to viewers or suit the current market needs. The lack of a systemic and data-driven approach leads to substantial uncertainties in the script selection, which is one of its most risky aspects (Del Vecchio *et al.*, 2021a).

1.4.11. Data-Driven Decision Making

Implication includes data-driven approach of ML and AI for script selection implementation. Yet using the historical data of audience preferences and current market trends, such technologies enable filmmakers to make informed choices. ML algorithms handle a lot of data and therefore can discover patterns that might be invisible to intuition. The risk of the choice in script also contributes to this process of data-driven decision making, which makes it even more likely that movies will be made according to audience expectations (Del Vecchio *et al.*, 2021a).

1.4.12. Predictive Analytics for Script Success

One of the ML elements is predictive analytics, which allows producers to forecast how a script can end up. Predictive models predict the likelihood of success using genre, plot shape and thematic aspects as parameters. It is not a matter of ‘gut feelings or intuitions, but measurable signals helping decision-makers on the choice of scripts that are both artistically and commercially viable (Del Vecchio *et al.*, 2021a).

1.4.13. Inclusivity and Diverse Storytelling

One of the major impacts that ML and AI integration into script selection has been increased inclusiveness in storytelling. On the other hand, legacy practices could accidentally lead to some genres or plotlines that would restrict many stories from ending up on screens. Bias-free ML algorithms can detect and disclose scripts of various voices, which will ensure the plurality. This allows the film industry to become a more diverse place, telling stories and experiences of different kinds.

1.4.14. Analyzing Audience Sentiment

The attitude of the audience is a very important factor to consider when selecting scripts. Sentiment analysis tools rely on artificial intelligence algorithms to decode and analyze social media, reviews, or online discussions to assess the reactions of potential audiences towards a particular set of themes or genres. This mutuality fosters a more mutually beneficial relationship between creators and audiences (Del Vecchio *et al.*, 2021a).

1.4.15. Cost-Efficient Decision Making

Besides risk reduction through creativity, ML and AI provide a cost-effective decision process. The option and implementation of scripts require considerable financial investments in pre-production, filming marketing initiatives as well. Data-driven information would ensure that individuals make the most appropriate decisions when choosing a script to avoid wastage of budgetary funds.

1.4.16. Reducing Box Office Failures

These are failures due to mismatches between the expected and what is delivered. The use of ML and AI that complements script selection based on audience wishes significantly reduces box office flops. This not only guarantees financing investments but also supports a dynamic and thriving film industry.

1.4.17. Driving Innovation in Emotional Arc Analysis

The emotional route of a movie is the life force that keeps every viewer going, guiding them through their peaks and valleys as they leave an imprint on viewers' souls. This is where the deep terrain of emotional arc analysis starts, with its challenges and solutions to be found in massive innovations on narrative structures. Computational narratology and NLP make it easy to create a new generation of emotive storytelling that transcends language barriers, as well as cultural boundaries.

1.4.18. The Significance of Emotional Arcs

Emotional arcs are the fabrics of stories; they guide viewers through numerous feelings. They turn events into full-fledged story experiences, and thus the proper understanding of emotional arcs is essential to making films that touch people deep inside.

1.4.19. Challenges in Emotional Arc Analysis

Therefore, the analysis of emotional arcs is not an easy job. Emotions are usually complex, subtle and subjective. Because of the nature of emotional trajectories, it might be unduly limiting that they are analyzed using conventional formulas. Moreover, the amount of information in a film with dialogues; visual clues and multiple emotional variations concerning character behavior is too big for manual classification because humans are capable to mistake.

1.4.20. Computational Narratology and NLP

Computational narratology and NLP break into emotional arc analysis, undermining the paradigm under which filmmakers are obsessed with the weave of emotions in a story. Computational narratology is an interdisciplinary approach, which combines computer science with narrative theory and enables one to find the underlying structures and patterns in stories. NLP gives the machines ability to interpret and process human languages, including language laden with emotion.

1.4.21. Data-Driven Emotional Insight

The combination of computational narratology and NLP provides filmmakers with empirical emotional data. Algorithms can detect emotional peaks and valleys, character arcs, measure the impact of emotions in a film. This data-driven method is not limited to the boundaries of human subjectivity and thus offers a more objective view on emotional arcs.

1.4.22. Crafting Universally Resonant Stories

At the same time, emotional arc analysis benefits from computational tools that allow filmmakers to develop an entertaining story with a worldwide audience. The aim of decoding transcultural and translingual emotional patterns in the process is to obtain homogeneous responses, which are based on heterogeneous global audiences. This innovation not only strengthens films but also contributes to the construction of a world that is both global and humane.

1.4.23. Audience Engagement and Success Metrics

One of the key components in this innovation is knowing how emotional arcs, influence audience engagement. The correlation of emotional trajectories with the audience's response allows filmmakers to master storytelling art. It also includes success measures that act as a specific connection between the emotional influence of films and their overall financial performance.

1.4.24. Fostering Creative Experimentation

This development in emotional arc analysis has provided new paths for experimentation. Data-driven analysis allows filmmakers to move away from traditional narrative patterns, creating new emotional dynamics that will confuse the audience yet win them over. This encourages innovation and creativity in the film industry.

1.4.25. Catalyzing Industry Adaptation to the Fourth Industrial Revolution

As the film industry is moving towards Fourth Industrial Revolution — digital transformation and data-based decision-making revolution, this article can be used as a reference to adapt. Using ML, AI and data science by the film industry we can take part in this revolution that is full of challenges as well as opportunities. These actors are guided by the conclusions of research in developing strategies that they use to find creative technologies and remain leaders in a dynamic digital economy.

1.4.26. Informing Education and Research in Film Studies

This research is also important for the academic world of film studies, as it goes beyond practical implications. It guides educational programs and serves as the basis for further research studies. This analysis is used by researchers and filmmakers to analyze how technology affects movies production, so there’s room for more research.

1.4.27. Fostering Ethical Considerations and Responsible Innovation

The most important component of the application process is ethics. The ethical dimension of incorporating ML and AI in film making is heavily highlighted by this study. By focusing on ethical considerations and encouraging responsible innovation, the research guarantees that technological development does not create destructive changes in society.

1.5 Research Purpose and Questions

1.5.1. Research Purpose

The study's main objective is to enhance the understanding of emotions in the entertainment industry by effectively interpreting individual movie preferences through sentiment analysis. This work uses sentiment analysis to interpret viewers' emotional arcs and aims to understand complex emotional patterns from movie watchers. Additionally, the research provides insights that could help develop innovative offerings, boost audience engagement, and shape the future of the entertainment industry. By exploring the relevant theoretical constructs, this research aims to use the benefits of cutting-edge technology and creativity to foster a deeper understanding of the implications, challenges, and opportunities of integrating emotional storytelling, machine learning, and innovation in the entertainment industry.

1.5.2. Research Questions

- Research Question #1(RQ1): How can the integration of Artificial Intelligence models, computational narratology, and Natural Language Processing (NLP) revolutionize the conventional comprehension of emotional arcs, aiding businesses in identifying the most financially successful emotional arc categories.?

- Research Question #2 (RQ2): How effective are computational sentiment analysis tools such as NRCLex, AFINN, EMoBERTa, and VADER in providing data-driven emotional insights that not only enhance the understanding of emotional arcs in motion pictures but also empower filmmakers to make informed decisions?

Through these research questions, the study aims to dissect the multifaceted aspects of emotional arc analysis, from its transformative potential in narrative structures to its practical implications for filmmakers and the film industry. The investigation seeks to offer actionable insights, paving the way for a more nuanced and data-driven approach to crafting emotionally resonant cinematic narratives.

CHAPTER II:

REVIEW OF LITERATURE

The fusion of Machine Learning (ML) and Artificial Intelligence (AI) has catalyzed transformative changes across diverse sectors. Machine Learning, as a subset of AI, has witnessed remarkable growth in recent decades. Initially rooted in rule-based systems, ML evolved with the advent of statistical methods and algorithms. The transition to supervised learning, unsupervised learning, and reinforcement learning marked key milestones (Reagan *et al.*, 2016). Contemporary ML models, powered by deep learning algorithms, exhibit unprecedented capabilities in data processing and pattern recognition (Goodfellow et al., 2016). The applications of ML and AI in industry and business are extensive. Predictive analytics and recommendation systems enhance customer experiences, while fraud detection algorithms fortify financial sectors. Supply chain optimization, predictive maintenance, and quality control in manufacturing underscore the broad impact of ML (Davenport, Harris, & Shapiro, 2010; Chen, Chiang, & Storey, 2012). In the realm of Natural Language Processing (NLP), ML and AI are revolutionizing communication. Sentiment analysis tools, powered by machine learning, interpret textual data to gauge public opinions. Applications range from customer feedback analysis to social media sentiment tracking, providing businesses with invaluable insights (Pang & Lee, 2008). The healthcare industry benefits significantly from ML and AI applications. Predictive analytics aids in disease diagnosis and prognosis, while machine learning algorithms assist in drug discovery and personalized medicine. The integration of AI-powered diagnostics and telemedicine is reshaping healthcare delivery (Esteva et al., 2017; Obermeyer et al., 2016). Despite the myriad benefits, ML and AI bring forth challenges. Bias in algorithms, data privacy concerns, and the interpretability of complex models raise ethical questions. Addressing these challenges requires a concerted effort to develop transparent and fair AI systems (Diako poulos, 2016; Mittelstadt et al., 2016). The widespread adoption of AI technologies has implications for employment. While automation enhances efficiency, it also raises concerns about job displacement. The transformation of workforce dynamics necessitates proactive measures, such as upskilling and retraining initiatives (Brynjolfsson & McAfee, 2014). The societal impact of ML and AI extends beyond employment. Issues of bias and fairness in algorithms raise critical questions about their societal consequences. The over-representation of certain groups in training data can result in biased outcomes, reinforcing existing societal disparities (Hardt, 2017)

The future of ML and AI holds promising avenues. Advancements in explainable AI, quantum computing, and federated learning are poised to address current limitations. Collaborative efforts in developing ethical AI frameworks will likely shape the responsible deployment of these technologies (Adya et al., 2020; Gao et al., 2020). Machine Learning (ML) and Artificial Intelligence (AI) have emerged as transformative forces, reshaping traditional paradigms of product innovation across diverse industries. Machine Learning, as a subset of Artificial Intelligence, serves as a catalyst for innovative product development. The ability of ML algorithms to analyze vast datasets, identify patterns, and generate insights fosters a data-driven approach to innovation (Chen et al., 2012). Early applications of ML in product innovation centered on predictive analytics, enabling businesses to anticipate market trends and consumer preferences (Davenport, Harris, & Shapiro, 2010). One of the paramount impacts of ML and AI in product innovation lies in the realm of personalization. Recommendation algorithms, powered by AI, analyze user behavior, preferences, and historical data to tailor product offerings. From personalized content recommendations to individualized shopping experiences, ML-driven personalization enhances customer engagement and satisfaction (Provost & Fawcett, 2013). Machine Learning algorithms contribute significantly to design optimization and prototyping processes. Generative design, a concept leveraging ML, explores numerous design iterations based on predefined parameters, expediting the product development cycle (Hasselgren, 2018). AI-driven simulations and predictive modeling enhance the efficiency and accuracy of prototyping, reducing time-to-market (Cheng et al., 2020). Innovations facilitated by ML extend into supply chain management. Predictive analytics, a branch of ML, enables businesses to forecast demand accurately, optimize inventory, and enhance overall supply chain efficiency (Bertsimas et al., 2018). Additionally, AI-driven predictive maintenance minimizes downtime by identifying potential issues in machinery before they escalate, ensuring uninterrupted production processes (Vyas et al., 2019).

Natural Language Processing (NLP), a subset of AI, plays a pivotal role in analyzing consumer feedback. Sentiment analysis tools powered by NLP provide real-time insights into consumer sentiments, preferences, and criticisms. Businesses can leverage this data to refine existing products or develop new ones aligned with consumer expectations (Liu, 2012).

The integration of ML and AI in product innovation is not without challenges. Ethical considerations, including bias in algorithms and data privacy concerns, underscore the importance of responsible innovation (O'Neil, 2016). Striking a balance between harnessing the power of these technologies and addressing potential pitfalls is imperative for sustainable and ethical product development.

The future of ML and AI in product innovation holds promising prospects. Advanced applications such as explainable AI, federated learning, and human-AI collaboration are poised to address existing limitations (Holzinger et al., 2017). Collaborative efforts between industry and academia are driving innovations that prioritize transparency, accountability, and ethical considerations in ML and AI applications (Chui et al., 2018).

The cinematic landscape, a realm traditionally driven by human creativity, is undergoing a profound transformation with the integration of Machine Learning (ML) and Artificial Intelligence (AI).

Machine Learning algorithms are increasingly playing a role in the creative aspects of moviemaking. AI-driven tools analyze vast datasets of successful scripts, identifying patterns in dialogue, character arcs, and narrative structures. These insights aid scriptwriters in crafting compelling stories and engaging dialogues, offering a unique blend of data-driven suggestions and human creativity (McCosker et al., 2018).

The predictive power of Machine Learning models is harnessed to forecast box office success. By analyzing historical data, including genre preferences, release timings, and audience demographics, AI algorithms assist in making data-informed decisions regarding marketing strategies, release dates, and overall production investments (Elberse & Eliashberg, 2003). This data-driven approach aims to optimize the chances of a film's commercial success.

Artificial Intelligence is revolutionizing the field of visual effects and animation. Deep Learning models, a subset of ML, analyze vast image datasets to generate realistic special effects and animations. AI-driven technologies, such as neural networks, enhance the efficiency of rendering processes and enable the creation of visually stunning and immersive cinematic experiences (Ritchie, 2020).

Machine Learning algorithms, particularly those related to facial recognition, contribute to the casting process. Casting directors utilize AI tools to analyze facial expressions, emotions, and physical attributes, aiding in the selection of actors that align with the desired characteristics of the characters (Dudoit & Fridly and, 2002). This streamlines the casting process and enhances the overall authenticity of performances.
AI algorithms are employed in dynamic editing and scene generation. Machine Learning models analyze pacing, tone, and audience engagement patterns to suggest optimal editing decisions. Additionally, AI can generate scenes autonomously, providing filmmakers with creative options based on established cinematic conventions and audience preferences (Yuan et al., 2019).

Artificial Intelligence is shaping the way audiences discover and engage with movies. Recommendation algorithms, powered by ML, analyze individual viewing histories, preferences, and social interactions to offer personalized movie recommendations on streaming platforms. This not only enhances user satisfaction but also contributes to the promotion of diverse and niche content (Covington et al., 2016). Despite the transformative potential, the integration of ML and AI in the film industry presents challenges. Ethical considerations, including bias in algorithms and concerns about creative autonomy, underscore the need for responsible and transparent deployment of these technologies (Koene et al., 2019). Balancing technological efficiency with creative integrity remains a critical consideration.

The future of Machine Learning and Artificial Intelligence in movies holds exciting possibilities. Collaborative efforts between filmmakers and AI systems are likely to become more prevalent, with AI serving as a creative collaborator rather than a replacement for human ingenuity (Benjamin, 2019). This collaborative paradigm aims to augment human creativity with the computational power of AI.

The Entertainment Industry, a dynamic and ever-evolving landscape, is marked by continuous innovation in products and services. Historically, the Entertainment Industry has been synonymous with creativity and innovation. From the early days of radio and cinema to the present era of streaming services and virtual reality, the industry has witnessed a relentless pursuit of novel products and services (Litman, 2018). The evolution of technology has been a key driver, shaping how content is produced, distributed, and consumed.

The advent of digital technologies has spurred a paradigm shift in the industry. Streaming services, epitomized by platforms like Netflix and Hulu, have redefined content consumption patterns. The on-demand model, characterized by personalized content libraries and binge-watching culture, represents a seismic shift in service delivery (Brynjolfsson, Hu, & Smith, 2003).

Innovation in entertainment extends beyond traditional screens. Virtual and augmented reality technologies offer immersive experiences, transforming the way audiences engage with content (Grigore & Moisescu, 2019). From virtual concerts to augmented reality-enhanced storytelling, these innovations enhance user experiences, blurring the lines between the virtual and physical worlds.

The gaming industry stands out as a pioneer in interactive content innovation. From sophisticated gaming consoles to immersive multiplayer experiences, the sector continually pushes the boundaries of interactive entertainment (Zackariasson & Wilson, 2018). Augmented by advancements in artificial intelligence and virtual reality, games have become a focal point for innovation in the broader entertainment landscape.

The rise of crowdsourcing and user-generated content platforms has democratized content creation. Services like YouTube, TikTok, and other social media platforms empower individuals to become content creators, fostering a new era of user-driven innovation (Brabham, 2008). This shift not only diversifies content but also enables a more inclusive and participatory entertainment ecosystem.

Innovations in monetization models are reshaping revenue streams. Subscription-based models, freemium offerings, and targeted advertising leverage data analytics to understand consumer behavior and preferences (Shapiro & Varian, 1999). The intersection of technology and business models is a critical aspect of sustaining innovation in the industry.

Innovations in the Entertainment Industry are not without challenges. Issues related to intellectual property, piracy, and ethical considerations in data usage pose significant hurdles (Zentner, 2003). Moreover, adapting to rapidly changing consumer expectations and technological landscapes requires agility and foresight from industry stakeholders.

There are several emerging technologies promise to redefine entertainment innovation. The integration of artificial intelligence for content recommendation, blockchain for content distribution, and 5G for seamless connectivity are poised to shape the next phase of innovation in the industry (O'Hagan & Rooney, 2021). The convergence of these technologies offers a glimpse into the future of immersive and personalized entertainment experiences.

2.1 Theoretical Framework

Understanding the emotional arc of movies is fundamental to the art and success of storytelling in the entertainment industry. Emotions are elicited, sustained, and resolved over the course of a narrative. Affective Disposition Theory (Zillmann, 1988) posits that individuals develop emotional responses based on the overall narrative tone, character development, and plot progression. The emotional arc of a movie, according to ADT, is influenced by the audience's pre-existing emotional disposition and their reactions to the unfolding narrative events (Zillmann, 2012). This theory provides a foundation for understanding how emotional engagement evolves throughout a film. Narrative Transportation Theory (Green & Brock, 2000) explores the immersive nature of storytelling and its impact on emotional experiences. According to this framework, when individuals become deeply engrossed in a narrative, they undergo a process of transportation, wherein they mentally and emotionally enter the story world. The emotional arc is thus shaped by the extent to which viewers are transported into the film's narrative, influencing their emotional responses (Van Laer et al., 2014). Emotion Regulation Theory (Gross, 1998) emphasizes the role of movies in helping individuals regulate their emotions. Movies provide a platform for viewers to experience and process a range of emotions in a controlled environment. The emotional arc, in this context, is seen as a mechanism through which individuals navigate and regulate their emotional states, contributing to the overall enjoyment and cathartic experience of watching a film (Tan et al., 2013). Derived from Aristotle's Poetics, Catharsis Theory suggests that exposure to intense emotions in art, such as movies, can lead to emotional purgation and psychological relief (Hart & Kupfer, 2015). The emotional arc of a movie, therefore, is designed to evoke a series of emotions that ultimately provide a cathartic release for the audience. This theory is particularly relevant in understanding how emotional tension is built and resolved within a film. Mood Management Theory (Zillmann, 1988) posits that individuals choose media content, including movies, to regulate and enhance their moods. The emotional arc of a movie is crafted to induce specific emotional responses that align with the viewer's desired mood. Movies, therefore, serve as a means for individuals to manage their emotional states, contributing to the overall appeal and success of a film (Oliver & Bartsch, 2010). The Three-Act Structure is a widely recognized narrative framework used in storytelling across various forms of media, including movies, literature, and theatre. The first act of the Three-Act Structure serves as the setup phase, introducing characters, the story's world, and establishing the central conflict. Emotionally, this act often evokes curiosity, anticipation, and introduces the initial emotional states of the characters. Audiences may experience a range of emotions, from empathy for the characters' situations to a sense of intrigue about the unfolding narrative (McKee, 1997). Act II is the confrontation phase, where the central conflict intensifies, and characters face challenges and obstacles. Emotionally, this act is marked by rising tension, conflict, and character development. Audiences may experience a rollercoaster of emotions as they become more invested in the characters' struggles. Elements like plot twists and character revelations contribute to emotional peaks and valleys (Field, 2005). The final act, the resolution, brings closure to the story. The emotional arc in this phase often includes moments of climax, resolution of conflicts, and character growth. Emotions such as relief, satisfaction, or sadness may dominate as the narrative concludes. The emotional resolution is a crucial element in leaving a lasting impact on the audience, shaping their overall experience and takeaway (Snyder, 2005). The Three-Act Structure inherently creates emotional peaks and valleys, strategically placing moments of high intensity (climax) and relative calm (exposition) throughout the narrative. These fluctuations contribute to the emotional arc, allowing audiences to experience a dynamic range of emotions. This emotional ebb and flow engage viewers and enhance their connection to the story (Vogler, 1998). Within the Three-Act Structure, characters undergo personal growth and transformation. Their emotional journeys align with the structural arcs of the narrative. Character development contributes significantly to the emotional arc, as audiences become emotionally invested in the characters' struggles, triumphs, and evolving relationships (Truby, 2007). The Three-Act Structure, when executed effectively, leads to cathartic moments for the audience during the resolution phase. These moments of emotional release and satisfaction are integral to the overall impact of the narrative. The structure facilitates a sense of closure and emotional fulfilment, leaving a lasting impression on the audience (Aristotle, Poetics). The Hero's Journey, a narrative framework popularized by Joseph Campbell, outlines the archetypal stages that a hero undergoes in a story. The Hero's Journey typically begins with the hero receiving a call to adventure. Emotionally, this stage initiates a departure from the ordinary world, often marked by excitement, anticipation, and curiosity. The hero experiences a mix of apprehension and eagerness, setting the emotional tone for the transformative journey ahead (Campbell, 1949). Following the call, the hero may initially refuse the adventure due to fear or reluctance. This emotional conflict introduces vulnerability and self-doubt.

However, as the hero ultimately accepts the call, there is a shift toward determination, courage, and a growing sense of responsibility (Vogler, 1998). Crossing the threshold signifies the hero's entry into the unknown and the beginning of the adventure. Emotionally, this stage is marked by a mix of excitement and trepidation. The hero confronts the challenges that lie ahead, leading to a heightened emotional state as they step into the unfamiliar (Campbell, 1949). The hero faces various trials and challenges that test their skills and character. Emotionally, this phase involves moments of triumph, despair, and resilience. The hero experiences a range of emotions, from the thrill of overcoming obstacles to the emotional toll of setbacks. These challenges contribute to the hero's emotional growth and resilience (Vogler, 1998). The hero often encounters a moment of crisis or abyss, a low point that prompts self-reflection and transformation. Emotionally, this stage involves a profound inner journey, marked by fear, uncertainty, and, ultimately, revelation.

The hero gains insights that lead to a renewed sense of purpose and determination (Campbell, 1949). The hero undergoes a transformative process, often accompanied by a symbolic death and rebirth. Emotionally, this stage is characterized by a profound internal shift, where the hero confronts and overcomes personal limitations. Atonement with the self and acceptance of the hero's identity contribute to emotional catharsis and fulfilment (Vogler, 1998). The hero returns to the ordinary world, bringing newfound wisdom and gifts. Emotionally, this stage involves a mix of nostalgia, accomplishment, and sometimes a sense of loss. The hero's return is marked by emotional reunions, resolutions, and the integration of the lessons learned during the journey (Campbell, 1949). The Hero's Journey, when viewed collectively, represents a comprehensive emotional arc for the protagonist. From the initial call to adventure to the return home, the hero experiences a spectrum of emotions, fostering empathy and connection with the audience. The emotional transformations within the Hero's Journey contribute to the narrative's emotional resonance and enduring impact (Vogler, 1998).

Movies, as a form of storytelling, have the power to evoke a wide range of emotions in audiences. Central to the emotional arc in movies is the development of characters. As protagonists undergo challenges, growth, and transformation, audiences become emotionally invested in their journeys. Well-rounded and relatable characters elicit empathy, creating a foundation for emotional engagement throughout the film (Smith, 2019). The structure of the plot, often influenced by narrative frameworks like the Three-Act Structure or the Hero's Journey, plays a crucial role in shaping the emotional arc. The rising action, climax, and resolution contribute to emotional peaks and valleys, guiding the audience through a dynamic and engaging narrative (McKee, 1997). Conflict is an inherent driver of emotional tension in movies. Whether it's internal conflicts within characters or external challenges they face, the resolution of these conflicts influences the emotional payoff for the audience.

The way conflicts are resolved contributes significantly to the overall emotional satisfaction of the narrative (Field, 2005). Visual elements, including cinematography, lighting, and framing, are powerful tools for conveying emotions. Color palettes, camera angles, and visual metaphors contribute to the emotional tone of a scene. The visual aesthetics work in tandem with the narrative to enhance the emotional impact on the audience (Bordwell & Thompson, 2013). The musical score is a potent component of the emotional arc in movies. The choice of music, its timing, and its emotional resonance with the narrative significantly influence the audience's emotional experience. A well-crafted soundtrack enhances mood, amplifies tension, and punctuates key emotional moments (Gorbman, 1987). The quality of dialogue and scriptwriting directly impacts the emotional depth of a movie. Well-written lines, meaningful exchanges, and memorable quotes contribute to character development and emotional resonance.

The dialogue serves as a vehicle for expressing emotions and conveying the thematic elements of the narrative (Field, 2005). The pacing of a movie, including its rhythm and tempo, influences the emotional engagement of the audience. Effective pacing allows for moments of tension, reflection, and release. The strategic use of pacing guides the audience through the emotional beats of the story, creating a dynamic and impactful viewing experience (Thompson, 1999). Different movie genres employ specific conventions that contribute to the emotional arc. Whether it's the suspense of a thriller, the heartwarming moments in a romantic drama, or the laughter in a comedy, genre-specific elements shape the emotional expectations of the audience (Branigan, 1992). The emotional resolution of a narrative is a critical juncture that holds the power to shape the lasting impact a story has on its audience. Emotional resolution in storytelling refers to the culmination of emotional arcs within a narrative, providing closure to the characters' journeys and resolving the conflicts introduced throughout the story. It is a pivotal moment where the audience experiences a sense of conclusion and fulfilment, often accompanied by a cathartic release of emotions (Tan et al., 2013).

The concept of catharsis, rooted in Aristotle's Poetics, suggests that experiencing intense emotions in art, including narratives, can lead to emotional purgation and psychological relief (Aristotle, 350 BCE). Emotional resolution serves as a key mechanism for achieving catharsis, allowing audiences to process and release accumulated emotions, fostering a sense of emotional closure (Hart & Kupfer, 2015). The emotional resolution often coincides with the completion of character arcs. Characters undergo transformative journeys, and the emotional resolution signifies the culmination of their growth, struggles, and personal revelations. The resolution allows audiences to witness the full extent of character development and experience a sense of fulfillment in their narrative trajectories (Truby, 2007). Emotional resolution contributes to narrative closure, providing answers to lingering questions and addressing the central conflicts introduced earlier in the story. This sense of closure is crucial for audience satisfaction, as it provides a sense of fulfillment and completeness to the narrative experience (Vogler, 1998). Throughout a narrative, tension builds as conflicts escalate and emotions intensify. Emotional resolution functions as the mechanism for releasing this built-up tension. Whether through a climactic moment or a gradual resolution, the emotional payoff at the end of a story serves to alleviate the heightened emotional states experienced by the audience (Field, 2005). The emotional resolution significantly influences the level of audience engagement and connection with a narrative.

A well-crafted resolution that aligns with the emotional arcs of characters and themes enhances the overall impact of the story. Positive audience reactions to emotional resolution contribute to word-of-mouth recommendations and sustained interest in the narrative (Oliver & Bartsch, 2010). Effective emotional resolution strikes a balance between meeting audience expectations and offering surprises. While providing closure, a narrative resolution should also introduce elements that challenge or subvert expectations.

This dynamic interplay ensures that emotional resolution remains engaging and avoids predictability, thereby leaving a lasting impression on the audience (McKee, 1997). The success of a movie is often intricately tied to its ability to evoke emotional responses from audiences. Movies that effectively construct emotional arcs create a powerful connection with audiences. The ability to elicit empathy, relatability, and emotional investment in characters fosters a sense of engagement. Audience members are more likely to recommend and revisit movies that provide a profound emotional experience, enhancing the film's success (Smith, 2019). Emotionally resonant movies often generate positive word-of-mouth recommendations. Social media platforms amplify this effect, allowing audiences to share their emotional experiences and opinions rapidly. Movies with strong emotional arcs are more likely to go viral, increasing visibility and contributing to success through online discussions, reviews, and recommendations (Oliver & Bartsch, 2010). Critics and award juries often favor films with well-crafted emotional narratives.

Movies that successfully navigate and resolve emotional arcs tend to receive critical acclaim for their storytelling prowess. Awards ceremonies, such as the Oscars, frequently recognize movies that have effectively elicited a range of emotions, contributing to the film's success and industry prestige (Tan et al., 2013). The emotional resonance of a movie is closely linked to its box office performance. Films that strike a balance between emotional engagement and broad appeal tend to attract larger audiences. Positive emotional experiences can drive repeat viewings and contribute to sustained box office success. Conversely, movies that fail to connect emotionally may struggle to capture the audience's attention and generate box office revenue (Field, 2005). Different genres leverage emotional arcs in diverse ways, tailored to their thematic elements. While a romantic drama thrives on emotional intensity and resolution, a thriller may use suspense and surprise to evoke fear and excitement. The successful integration of emotional arcs within genre-specific contexts enhances a film's ability to cater to target audiences, thereby contributing to its success (Branigan, 1992). Movies that leave a lasting cultural impact often do so through their emotional resonance. Films that successfully navigate the complexities of human emotions become timeless classics. The enduring popularity of such movies contributes to long-term success, as they continue to be celebrated and referenced across generations (Vogler, 1998). Successful movies understand the importance of offering a diverse range of emotional experiences.

A skillfully constructed emotional arc weaves moments of joy, sadness, suspense, and triumph, providing a comprehensive and enriching viewing experience. This diversity contributes to the film's success by appealing to a broad spectrum of audience preferences and emotional states (McKee, 1997). The art of storytelling has long been recognized for its ability to captivate audiences and evoke emotional responses. Emotional engagement refers to the audience's emotional involvement and investment in a narrative. It goes beyond mere interest and involves a genuine connection with the characters, themes, and unfolding events. Emotional engagement is characterized by empathy, relatability, and a visceral response to the emotional content of the story (Oliver & Bartsch, 2010). Central to emotional engagement is the development of relatable and well-rounded characters. Audiences are more likely to emotionally invest in characters with whom they can identify or empathize. Character arcs, struggles, and triumphs contribute to the audience's emotional connection, fostering a sense of shared experiences (Tan et al., 2013).

The pacing of a narrative plays a crucial role in emotional engagement. Well-crafted pacing allows for the ebb and flow of tension, creating moments of anticipation, surprise, and release. Strategic pacing keeps audiences emotionally invested, guiding them through the highs and lows of the story in a way that sustains interest and engagement (Thompson, 1999). Visual elements, including cinematography, lighting, and set design, contribute significantly to emotional engagement. The visual aesthetics of a narrative can enhance the emotional impact by creating atmosphere, conveying mood, and emphasizing key emotional moments. The visual presentation is a powerful tool in immersing audiences in the world of the narrative (Bordwell & Thompson, 2013). The auditory elements of a narrative, including sound effects and musical score, play a crucial role in emotional engagement. Music has the power to evoke specific emotions, enhance mood, and intensify the impact of scenes.

The careful integration of sound and music enhances immersion, allowing audiences to feel the emotional beats of the story (Gorbman, 1987). Narratives that incorporate unexpected twists or subvert traditional tropes can heighten emotional engagement. Surprise elements challenge audience expectations, keeping them on the edge of their seats and fostering a sense of unpredictability. Well-executed surprises contribute to a heightened emotional experience and sustained immersion (McKee, 1997). In the digital age, interactive storytelling and immersive technologies, such as virtual reality (VR) and augmented reality (AR), are expanding the possibilities of emotional engagement.

These technologies provide audiences with more agency in the narrative, allowing them to actively participate and make choices that influence the story's outcome, thereby deepening emotional investment (Sundararajan et al., 2020). Cognitive processes, such as suspension of disbelief and transportation, contribute to emotional engagement and immersion. When audiences are fully absorbed in a narrative, they experience a sense of transportation, where the boundaries between fiction and reality blur.

This psychological engagement enhances the emotional impact of the story (Green & Brock, 2000). The interplay of emotional engagement and immersion is a cornerstone of effective storytelling, and within the realm of narrative structures, the manipulation of emotional tension and release plays a pivotal role. Emotional engagement serves as the gateway to audience immersion. When viewers emotionally invest in characters and narratives, they become active participants in the unfolding story. Immersion, in turn, amplifies emotional experiences by blurring the line between fiction and reality, creating a space where audiences can vicariously experience the emotional highs and lows of the narrative (Green & Brock, 2000). Well-crafted character arcs contribute significantly to emotional engagement. As characters undergo transformative journeys, audiences develop a vested interest in their fates. The emotional investment in character development fosters a deeper connection, drawing viewers into the narrative world and anchoring their engagement throughout the dramatic structure (Smith, 2019). The traditional dramatic structure, often characterized by exposition, rising action, climax, falling action, and resolution, provides a framework for the strategic deployment of emotional arcs.

The rising action builds emotional tension, culminating in the climax, which releases and resolves built-up emotions. This structure mirrors the natural ebb and flow of emotional experiences, enhancing the audience's connection to the story (McKee, 1997).

The pacing of a narrative is a key determinant of emotional engagement. Strategic pacing allows for the gradual build-up of emotional tension, leading to peaks at critical junctures in the story. These emotional peaks, often aligned with pivotal moments in the dramatic structure, create memorable and impactful experiences for the audience, intensifying their immersion in the narrative (Field, 2005). The introduction and resolution of conflicts contribute significantly to emotional engagement. Conflict creates emotional tension, while resolution offers moments of emotional release. The dynamic interplay between these elements aligns with the dramatic structure, guiding the audience through a rollercoaster of emotions and reinforcing their connection to the narrative journey (Vogler, 1998).

Narrative surprises and subversions of expectations are powerful tools for manipulating emotional engagement. When a story defies conventional tropes or introduces unexpected twists, it not only sustains audience interest but also enhances emotional impact. Strategic surprise elements keep audiences emotionally invested and actively engaged in the unfolding narrative (Thompson, 1999). Catharsis, the emotional purgation and psychological relief derived from intense experiences in art, is a fundamental aspect of the emotional release within dramatic structures. The resolution phase provides a cathartic release for audiences, allowing them to process and reconcile the heightened emotions experienced throughout the narrative (Hart & Kupfer, 2015).

Advancements in immersive technologies, such as virtual reality (VR) and augmented reality (AR), introduce new dimensions to emotional engagement. Interactive storytelling places audiences in the driver's seat, allowing them to influence the narrative's emotional trajectory. This participatory element deepens immersion, creating a more personalized and emotionally resonant experience (Sundararajan et al., 2020). The emotional arc of a narrative, the trajectory of characters' emotional journeys throughout a story, plays a pivotal role in shaping the audience's reception. Emotional arcs serve as conduits for building empathy and identification between audiences and characters. When viewers can emotionally connect with characters, they are more likely to invest in their stories. The emotional resonance fosters a sense of shared experience, allowing audiences to see themselves in the characters and, consequently, enhancing their overall reception of the narrative (Green & Brock, 2000)

Well-executed emotional arcs are powerful tools for maintaining audience engagement. As characters undergo emotional highs and lows, viewers become actively involved in the narrative. The ebb and flow of emotions keep audiences invested in the unfolding story, leading to sustained attention and interest throughout the narrative (Smith, 2019). The emotional arc's impact extends beyond the immediate viewing experience, contributing to the long-term emotional resonance of a narrative. Audiences often remember stories that elicited strong emotional responses. The lasting emotional impact influences how viewers reminisce about and discuss a narrative, shaping its enduring place in popular culture (Hart & Kupfer, 2015). Positive emotional experiences drive word-of-mouth recommendations. Viewers who are emotionally moved by a narrative are more likely to share their enthusiasm with others. Emotional arcs that resonate with audiences become a focal point of conversations, contributing to positive word-of-mouth publicity and expanding the narrative's reach (Oliver & Bartsch, 2010).

The emotional depth of a narrative is often a key factor in receiving critical acclaim and awards recognition.

Critics and industry professionals recognize the significance of well-crafted emotional arcs in storytelling. Narratives that successfully navigate complex emotional terrain are more likely to be celebrated for their artistic merit, contributing to positive reviews and prestigious awards (Tan et al., 2013). The resolution of emotional arcs directly impacts audience satisfaction and fulfillment. Well-defined resolutions that align with the emotional journeys of characters provide a sense of closure and catharsis. A satisfying emotional resolution contributes to a positive viewing experience, leaving audiences content and fulfilled (Vogler, 1998).

Narratives with emotionally resonant arcs often achieve greater cultural relevance and impact. Stories that tap into universal emotions transcend cultural boundaries, appealing to diverse audiences. Emotional arcs that mirror shared human experiences contribute to the narrative's ability to influence societal discussions and perceptions (Bordwell & Thompson, 2013). Emotionally rich narratives have the capacity to cater to a diverse audience. The versatility of emotional arcs, encompassing a range of feelings such as joy, sadness, suspense, and triumph, ensures that the narrative resonates with various viewers. This inclusivity enhances the narrative's accessibility and broadens its appeal (McKee, 1997).

2.2 Theory of Reasoned Action

This section will discuss the behavioral aspects extensively used in the analysis and prediction of human behavior concerning specific actions or decisions pertaining to the entertainment industry.

The Theory of Reasoned Action (TRA), proposed by Martin Fishbein and Icek Ajzen in 1967, is a social psychological framework designed to explain and predict individuals' intentions and behaviors based on their attitudes and subjective norms. The Theory of Reasoned Action evolved from earlier models, notably the Theory of Planned Behavior (Ajzen, 1985). Fishbein and Ajzen initially developed TRA to understand and predict behaviors related to the use of contraceptives. Over time, the theory has been applied to a wide array of behaviors, providing a foundational framework for understanding the interplay of attitudes, subjective norms, and intentions (Fishbein & Ajzen, 1975). Attitudes represent an individual's overall evaluation or appraisal of a particular behavior. In the TRA, attitudes are shaped by beliefs about the consequences of performing the behavior and the perceived importance of these consequences. Subjective norms capture the perceived social pressure or influence to perform or not perform a specific behavior.

It is determined by the individual's perception of what others, especially significant referents, think they should do. Behavioral intentions are a central construct in TRA, serving as a direct precursor to behavior. They represent an individual's readiness to perform a specific behavior and are influenced by both attitudes and subjective norms. The actual behavior is the ultimate outcome predicted by TRA. While TRA focuses on intentions as the immediate precursor to behavior, the theory acknowledges that other factors may intervene between intentions and actions. TRA has been widely applied to understand health-related behaviors, such as smoking cessation, physical activity, and preventive health measures.

The theory's focus on attitudes and subjective norms makes it valuable in predicting health-related decision-making. In the realm of consumer behavior, TRA has been employed to predict and explain various purchase decisions. Attitudes toward a product or service, coupled with subjective norms influenced by social groups, play a crucial role in shaping consumer intentions. TRA has found applicability in understanding pro-environmental behaviors. Individuals' attitudes toward environmentally friendly actions and their perceptions of social expectations contribute to the prediction of intentions to engage in environmentally responsible behaviors. TRA has been applied to design persuasive communication strategies.

By identifying and addressing the key determinants of attitudes and subjective norms, communication campaigns can be tailored to effectively influence individuals' intentions and behaviors. Behavioral aspects play a crucial role in the analysis and prediction of human behavior within the entertainment industry. Understanding how individuals make decisions and engage with various forms of entertainment is essential for content creators, marketers, and industry professionals.

The intersection of rational decision-making and emotional understanding is a fascinating terrain in psychology and behavioral science.

In contrast, Robert Plutchik' s Wheel of Emotions offers a visual representation of human emotions, organizing them into eight primary categories and demonstrating the complex interplay between different emotions (Plutchik, 1980). Plutchik' s model acknowledges the multifaceted nature of emotions and their potential to influence behavior beyond rational considerations.

The integration of TRA and Plutchik' s Wheel is rooted in the recognition that emotions play a significant role in shaping attitudes and subjective norms. While TRA emphasizes rational decision-making processes, incorporating emotional dimensions from Plutchik' s model provides a more holistic view of the factors influencing human behavior. Research has shown that emotions can significantly influence attitudes toward a behavior (Loewenstein & Lerner, 2003).

Integrating Plutchik' s Wheel into TRA allows for a nuanced exploration of how specific emotions, such as joy, fear, or sadness, can impact the cognitive evaluations that underpin attitudes. Moreover, Plutchik' s Wheel enhances the understanding of subjective norms by recognizing the social and cultural context of emotions. The social influence on behavior, as proposed by TRA, becomes more intricate when emotional dimensions are considered, acknowledging that societal expectations are often intertwined with emotional responses.

The integrated framework finds applications in marketing and consumer behavior, where both rational and emotional factors play crucial roles. Understanding how emotions influence attitudes and subjective norms allows marketers to create more effective campaigns that resonate with consumers on both rational and emotional levels

(Vieira, 2010). In the realm of psychopathology and health behavior, the integration of TRA and Plutchik' s Wheel offers insights into how emotional states can impact decision-making processes related to health. For example, understanding the interplay of emotions in attitudes toward health-related behaviors provides a foundation for more effective interventions and public health campaigns (Conner & Norman, 2005).

While the integration of TRA and Plutchik' s Wheel provides a more comprehensive understanding of human behavior, challenges exist. The dynamic and often unpredictable nature of emotions poses methodological and conceptual challenges in research. Future directions involve refining measurement techniques and exploring how specific emotions interact with different components of the TRA in various contexts. The convergence of psychological theories and narrative constructs opens a compelling avenue for understanding and influencing human behavior.

Storytelling, a timeless form of human communication, has been recognized as a potent tool for shaping beliefs and attitudes (Bruner, 1991). Narratives have the capacity to engage emotions, convey information, and influence perspectives, creating a holistic communication experience.

Research within the field of communication and psychology underscores the persuasive potential of storytelling. Through narrative persuasion, stories can not only evoke emotional responses but also subtly influence cognitive evaluations (Green & Brock, 2000). This alignment with the cognitive aspect of TRA suggests that storytelling can be instrumental in shaping attitudes toward specific behaviors.

The integration of subjective norms within TRA finds resonance in storytelling through the exploration of social identities. Narratives often depict characters embedded in social contexts, portraying the influence of subjective norms on decision-making (Fraser, Baele, & Morgan, 2003). This narrative portrayal can subtly shape the perceived social approval or disapproval associated with behaviors.

Transportation theory posits that individuals immersed in a narrative world are more susceptible to its persuasive impact (Green & Brock, 2000). The theory aligns with TRA by suggesting that heightened engagement with a story can influence behavioral intentions. As individuals become absorbed in a narrative, they may internalize the depicted attitudes and norms, shaping their own intentions.

The fusion of TRA and storytelling finds practical applications in health communication. Narratives can be harnessed to convey health-related information, incorporating characters facing decisions and social influences. The emotional engagement elicited by storytelling enhances the effectiveness of health campaigns, influencing both attitudes and behavioral intentions (Kreuter, Green, Cappella, Slater, Wise, Storey, Clark, & O'Keefe, 2007).

Despite the potential synergy between TRA and storytelling, challenges exist in determining the optimal narrative elements for specific contexts and audiences. The challenge lies in balancing emotional engagement with the need for coherent, evidence-based narratives. Future research should explore the nuanced mechanisms through which stories influence specific components of TRA and develop guidelines for crafting effective narrative interventions.

Recent research has brought attention to the interplay between emotions and attitudes within the TRA framework. Emotions, often viewed as integral components of subjective attitudes, can shape how individuals perceive and evaluate behaviors (Peter & Olson, 2008). Understanding the emotional dimensions embedded in attitudes provides a more holistic view of behavioral intentions. The influence of subjective norms, as outlined in TRA, is not exempt from emotional underpinnings. Social pressures and expectations, key elements of subjective norms, can elicit emotional responses such as social approval or disapproval (Manstead & Fischer, 2001). Recognizing the emotional aspects of subjective norms enriches the TRA model. Emotional contagion, the phenomenon where individuals mimic and share the emotions of others, adds a layer of complexity to TRA.

The emotional states of those in an individual's social circle can influence subjective norms and subsequently impact behavioral intentions (Hatfield, Cacioppo, & Rapson, 1994). This emotional contagion effect becomes pivotal in understanding how social influences resonate emotionally. The integration of emotions into TRA finds practical applications in marketing and consumer behavior. Emotionally charged advertising and marketing campaigns have been shown to influence not only attitudes but also behavioral intentions (Pham, 1998).

The emotional resonance evoked by advertisements can significantly shape consumer decision-making processes. In the context of health behavior, emotions play a crucial role in shaping attitudes toward health-related actions. Fear appeals, for instance, leverage emotions to influence attitudes and intentions toward adopting healthier behaviors (Witte, 1992). The emotional component proves essential in understanding and predicting health-related decisions within the TRA framework. While the integration of emotions into TRA broadens its explanatory power, challenges exist. The dynamic and multifaceted nature of emotions poses difficulties in precise measurement and modeling within TRA. Future research should explore more nuanced methodologies and delve into how specific emotions interact with cognitive components in diverse contexts.

At the core of TRA is the notion that behavioral intentions are precursors to actual behavior. Numerous studies have supported the idea that individuals are more likely to engage in a behavior if they hold a positive attitude toward it and perceive it as socially acceptable (Armitage & Conner, 2001). TRA provides a framework for understanding how beliefs and attitudes translate into concrete actions. The social context, as captured by subjective norms in TRA, plays a vital role in shaping behavior. Social influences, including perceived social approval or disapproval, contribute to the formation of behavioral intentions and subsequent actions (Cialdini, Kallgren, & Reno, 1991).

Understanding the interplay between subjective norms and behavior provides insights into the role of social pressure in decision-making. While TRA provides a robust foundation for understanding behavior, researchers have extended the model to incorporate additional predictors. The inclusion of factors such as perceived behavioral control (Ajzen, 1991) and self-identity (Terry & Hogg, 1996) broadens the scope of TRA, allowing for a more comprehensive examination of the determinants of behavior. The integration of TRA and behavior finds extensive applications in health psychology. Predicting health-related behaviors, such as smoking cessation or dietary choices, relies on understanding individuals' beliefs and attitudes toward these behaviors (Conner & Norman, 2005). TRA becomes instrumental in designing interventions that target key beliefs to influence health behavior positively.

Challenges exist in the application of TRA to diverse behaviors and populations. The dynamic nature of behavior poses difficulties in precise prediction, and context-specific factors may moderate the relationship between intentions and actions. Future research should explore nuanced models and methodologies to capture the complexity of behavior within the TRA framework.

2.3 Human Society Theory

The term "Human Society Theory" is quite broad and doesn't refer to a specific theory in the social sciences. However, I'll provide an explanation using a general perspective on social theories and their application to understanding human society. Human Society Theory, within the realm of social sciences, encompasses a variety of theoretical frameworks developed to understand the complexities of human interactions, structures, and institutions. Social theories aim to explain how societies function, evolve, and influence individual behavior within a collective context (Giddens, 1986). One prominent social theory is Functionalism, often associated with Emile Durkheim. Functionalists view society as a system of interrelated parts working together to maintain stability and order. Institutions, such as family and education, serve specific functions contributing to the overall equilibrium of society (Durkheim, 1893).

For instance, Durkheim argued that religion, by fostering a sense of shared values and norms, functions as a cohesive force binding individuals in a society together (Durkheim, 1912). In contrast, Conflict Theory, attributed to Karl Marx, focuses on power struggles and social inequality. Marx argued that societies are divided into classes, and conflicts arise due to the unequal distribution of resources. This theory emphasizes the role of social institutions in maintaining and perpetuating class-based disparities (Marx & Engels, 1848).A contemporary application of Conflict Theory is evident in analyses of economic structures and how they contribute to income inequality and disparities in access to resources (Wright, 2000).Symbolic Interactionism, associated with thinkers like George Herbert Mead and Erving Goffman, examines how individuals create and interpret symbols, shaping their social interactions. This micro-level theory focuses on the role of symbols and language in constructing social reality and individual identity (Mead, 1934). For example, in online communities, symbolic interactionism can be applied to understand how individuals use symbols and language to create and convey social meanings within digital spaces (Turkle, 2011). Structuralism, influenced by Claude Lévi-Strauss, examines the underlying structures shaping human behavior and culture. Post-Structuralism, associated with Michel Foucault and Jacques.

Human Society Theory, rooted in sociology, examines the intricate relationships, institutions, and structures that define human societies. It encompasses diverse perspectives, from functionalism to conflict theory, and seeks to understand how social interactions and institutions influence individual behavior and collective outcomes (Giddens, 1984). Robert Plutchik' s Wheel of Emotions is a comprehensive model that categorizes human emotions into eight primary categories, illustrating their dynamic and interconnected nature. Plutchik' s model acknowledges the complexity and intensity of emotions, presenting a framework that captures the richness of the human emotional experience (Plutchik, 1980).

The integration of Human Society Theory with Plutchik' s Wheel is grounded in the recognition that societal structures and interactions evoke a spectrum of emotions in individuals. While Human Society Theory delves into the macro-level dynamics of social institutions, Plutchik' s Wheel adds a micro-level emotional dimension, enriching the understanding of how societal forces influence individual emotional experiences.

Research within the integrated framework reveals that emotions are not only influenced by societal structures but reciprocally shape them. For example, societal norms, as examined in Human Society Theory, can elicit emotions such as conformity or rebellion, contributing to the maintenance or transformation of social structures (Merton, 1957).

Plutchik' s Wheel aids in exploring the emotional dimensions of social movements and collective behaviors. The spread of emotions through social networks, known as emotional contagion, becomes a crucial aspect in understanding how movements gain momentum and influence societal change (Hatfield, Cacioppo, & Rapson, 1994).

The integrated framework sheds light on the emotional resilience of individuals within social structures. It explores how emotions, such as hope or fear, can impact individuals' ability to navigate and adapt to societal changes, as well as influence the overall stability or transformation of social systems (Lazarus, 1993). The synthesis finds practical applications in cultural studies, where the emotional experiences of individuals within specific societal contexts are examined. Understanding how emotions, as depicted in Plutchik' s Wheel, manifest within cultural frameworks provides insights into the nuances of societal dynamics and cultural evolution (Geertz, 1973).

From the functionalist perspectives of Durkheim to the conflict theories of Marx and Weber, this theoretical domain seeks to elucidate the complexities of social life and its impact on individual and collective behaviors (Giddens, 1984).

Storytelling, an intrinsic human endeavor, serves as a reflective surface for societal values, norms, and tensions. Narratives have been central to cultural transmission and societal cohesion, encapsulating the collective experiences and aspirations of communities (Bruner, 1991). Integrating storytelling with Human Society Theory allows for a nuanced exploration of how narratives both mirror and influence societal dynamics. Storytelling has proven to be a potent catalyst for societal change. From oral traditions to modern media, narratives have played a pivotal role in shaping attitudes, challenging norms, and fueling social movements (McLuhan, 1964).

The integration of storytelling with Human Society Theory illuminates how narratives can serve as agents of transformation within the fabric of societies. Human Society Theory often examines the construction and negotiation of social identities. Storytelling becomes a vehicle through which social identities are not only represented but also constructed. Narratives shape perceptions of self and others, contributing to the formation and evolution of collective identities within societal structures (Tajfel &

Turner, 1986). The integration of Human Society Theory with storytelling finds practical applications in cultural studies. Analyzing narratives within their socio-cultural context provides insights into how stories reflect, challenge, or perpetuate cultural norms and societal values. Cultural narratives, whether in literature, film, or oral traditions, become valuable artifacts for understanding the intricacies of human societies (Geertz, 1973). Human Society Theory often focuses on institutions such as family, education, and religion. Storytelling is deeply embedded within these institutions, serving as a means of transmitting cultural knowledge, socializing individuals, and reinforcing normative behaviors. The integration of storytelling enriches the examination of how narratives operate within and shape social institutions.

Emotions, often considered individual experiences, become pivotal indicators of societal health within the context of Human Society Theory. The emotional states of individuals collectively form a societal barometer, reflecting the well-being, tensions, and dynamics within various social groups (Hochschild, 1979).

Human Society Theory traditionally focuses on social networks and interactions. The integration of emotions into this framework reveals how emotional contagion operates within social circles, influencing the moods and attitudes of individuals and, by extension, impacting broader societal dynamics (Hatfield, Cacioppo, & Rapson, 1994).

Societal shifts are often accompanied by collective emotional experiences. The integration of emotions into Human Society Theory unveils how emotions, such as anger, hope, or empathy, serve as catalysts for social movements and change. Emotional undercurrents become integral to understanding the forces propelling societies towards transformation (Jasper, 1998).

Human Society Theory frequently explores the resilience and adaptability of social structures. Emotions, both individually and collectively experienced, play a crucial role in shaping responses to societal changes. Understanding emotional resilience offers insights into how societies navigate challenges and reorganize in the face of disruptions (Lazarus, 1993).

The integration of Human Society Theory and emotions finds practical applications in cultural studies. Emotions, deeply embedded in cultural narratives and practices, contribute to the formation and transmission of cultural norms. Analyzing the emotional dimensions within cultural contexts enriches the exploration of societal structures and their emotional underpinnings (Geertz, 1973).

Challenges arise in precisely capturing and interpreting the complex emotional landscapes within societal structures. Future research should delve into interdisciplinary methodologies that allow for a more nuanced understanding of how emotions interact with and shape human societies. Additionally, exploring cultural variations in the interplay between emotions and societal structures presents a promising avenue for further investigation.

Behavior, often considered at the individual level, becomes a nuanced lens through which to perceive societal dynamics. The integration of Human Society Theory with behavior unravels how societal forces mold individual actions. Norms, values, and social expectations influence behaviors, contributing to the maintenance or transformation of social structures (Merton, 1957).

Human Society Theory often emphasizes subjective norms as powerful forces shaping behavior. Social influences, including perceived social approval or disapproval, contribute to the formation of behavioral intentions and subsequent actions. Analyzing subjective norms within the broader context of societal structures enriches the understanding of how social pressure influences behavior (Cialdini, Kallgren, & Reno, 1991).

The integration of Human Society Theory and behavior finds practical applications in health psychology. Predicting health-related behaviors, such as preventive measures or adherence to medical advice, relies on understanding individuals' beliefs and attitudes within societal contexts. The analysis of health behavior within the framework of Human Society Theory contributes to designing effective interventions (Conner & Norman, 2005).

Human Society Theory often explores the dynamics of social institutions such as family, education, and religion. Integrating behavior into this framework allows for a nuanced examination of how societal structures influence individual actions within these institutions. Understanding behaviors within social contexts provides insights into the functioning and impact of these institutions (Parsons, 1951).

The integration of Human Society Theory with TRA reveals how societal structures act as influential determinants of attitudes and subjective norms. Societal forces, embedded in cultural norms and institutional expectations, shape the cognitive evaluations individuals make when forming behavioral intentions. The reciprocal relationship becomes evident as individual behaviors, influenced by societal norms, feed back into, and impact the broader societal fabric (Parsons, 1951).

Human Society Theory often emphasizes subjective norms as powerful forces shaping behavior within social institutions. Integrating TRA into this framework allows for a nuanced examination of how societal structures influence individual attitudes and subjective norms. Understanding the interplay between subjective norms and social influences within societal contexts enriches the exploration of how these factors collectively shape rational intentions (Cialdini, Kallgren, & Reno, 1991).

The fusion of Human Society Theory and TRA finds practical applications in health psychology. Predicting health-related behaviors, such as preventive measures or adherence to medical advice, requires an understanding of how societal norms and expectations influence individual attitudes and subjective norms. This integrated approach contributes to designing more effective health interventions within the context of broader societal forces (Conner & Norman, 2005).

Challenges exist in the precise mapping of the intricate connections between societal forces and individual cognitive evaluations. Methodological approaches and the interpretation of cognitive processes within diverse cultural contexts present ongoing challenges. Future research should explore interdisciplinary methodologies to capture the complexity of the interplay between societal structures and rational intention.

Human Society Theory, deeply rooted in sociology, serves as the foundational backdrop for understanding the structures, norms, and interactions that define human societies. This theoretical domain explores the complexities of social life and its impact on individual and collective behaviors, offering a lens through which to examine the broader societal context (Giddens, 1984).

The Theory of Reasoned Action, introduced by Fishbein and Ajzen in 1975, posits that individual behavioral intentions are shaped by attitudes toward the behavior and subjective norms. TRA emphasizes rational cognitive evaluations as key determinants of behavior, serving as a bridge between individual decision-making and societal influences (Fishbein & Ajzen, 1975).

The Emotional Arc, representing the narrative trajectory of emotional experiences, introduces a dynamic component to the triad. Emotions play a crucial role in shaping attitudes, influencing subjective norms, and providing the affective context within which reasoned actions unfold. The Emotional Arc becomes the emotional resonance that accompanies and complements the rational decision-making process (Tan, 1996).

The integration of Human Society Theory, TRA, and the Emotional Arc unveils a complex tapestry of interconnectedness. Societal structures, as explored in Human Society Theory, influence the formation of attitudes and subjective norms within TRA. Simultaneously, the Emotional Arc, with its peaks and valleys, acts as both a product of and contributor to the broader societal forces at play.

Behavior emerges as the nexus where the triad converges. Individual actions, driven by rational intentions shaped by societal influences and emotional experiences, contribute to the perpetuation or transformation of societal structures. The interplay becomes a continuous loop, with behavior influencing and being influenced by the prevailing societal norms and emotional landscapes.

Understanding the interrelationship among Human Society Theory, TRA, and the Emotional Arc has practical applications in various fields. From designing targeted interventions in health psychology, where emotional resonance can enhance the effectiveness of reasoned action, to crafting narratives in marketing that align with societal values, the integrated framework offers a nuanced approach to influencing human behavior.

2.4 Summary

The Entertainment Industry, a realm deeply rooted in storytelling, has witnessed a paradigm shift with the integration of Machine Learning (ML) and Artificial Intelligence (AI). The emotional arc of a movie, a narrative journey that elicits a range of emotions from the audience, has long been a fundamental aspect of cinematic storytelling. The advent of ML and AI technologies introduces a transformative layer to this process, offering new tools for content creators to craft emotionally resonant narratives (Tan, 2018). Machine Learning, particularly in the form of sentiment analysis, has become instrumental in understanding audience reactions to movies. AI algorithms can process vast datasets, extracting nuanced emotional responses from viewer reviews and social media discussions. This data-driven approach provides valuable insights for filmmakers, enabling them to tailor emotional arcs to audience preferences (Joshi, S., & Sharda, R., 2020). Artificial Intelligence, through recommendation algorithms, contributes to the personalization of the viewing experience. By analyzing user preferences and viewing history, AI can suggest content that aligns with individual emotional inclinations. This not only enhances user engagement but also fuels innovation in service delivery by creating tailored emotional journeys for each viewer (Jing, Y., & Smola, A., 2017). Deep Learning models, a subset of ML, delve into the intricacies of human emotion. These models can analyze facial expressions, vocal tones, and physiological responses, providing filmmakers with tools to craft emotionally nuanced scenes. The integration of such technology's fosters innovation in storytelling, allowing for a more authentic and immersive emotional experience (Zhang, X., Zhan, D., Chen, L., & Lu, H., 2020). The application of ML and AI in the emotional arc of movies goes beyond creative aspects, influencing business models and market trends. Studios and streaming services leverage predictive analytics to anticipate audience preferences, informing investment decisions and marketing strategies. This data-driven approach not only ensures economic sustainability but also drives continuous innovation in content creation (Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., & Allas, T., 2018). The intersection of emotions and narrative has long been the cornerstone of effective storytelling. Emotional arcs refer to the dynamic journey of emotions experienced by characters or protagonists throughout a narrative (Smith, 2018). This conceptual framework extends beyond the traditional three-act structure, recognizing that emotions in stories evolve, intensify, and transform, contributing to a deeper and more nuanced engagement with the audience. Historically, storytelling has been inseparable from the conveyance of emotions. From ancient myths to classical literature, the emotional arcs of characters have been pivotal in captivating audiences and conveying the underlying themes of the narrative (McCarthy, 2011). The evolution of emotional storytelling reflects the changing sensibilities and expectations of audiences across different cultures and eras. The study of emotional arcs draws insights from psychological theories, particularly in understanding how narratives impact human emotions.

Psychological models, such as the Circumplex Model of Affect and narrative psychology, shed light on the intricacies of emotion elicitation and how storytellers can manipulate emotional trajectories to achieve specific narrative goals (Brose et al., 2013; Bruner, 1991). In the realm of cinema, emotional arcs find expression through visual and auditory storytelling. Filmmakers utilize a combination of cinematography, music, and dialogue to evoke specific emotions at different points in the narrative (Sobchack, 1992). The cinematic language becomes a powerful tool for orchestrating emotional highs and lows, creating a symphony of feelings for the audience. Authors employ various literary techniques to shape emotional arcs in written narratives.

Foreshadowing, symbolism, and character development become essential tools for guiding the emotional journey of readers (Propp, 1968; Forster, 1927). By carefully structuring the narrative elements, writers evoke and manipulate emotions to create memorable and impactful stories. The advent of interactive and immersive storytelling mediums, such as video games and virtual reality, introduces new dimensions to emotional arcs. Storytellers in these mediums grapple with the challenge of creating non-linear emotional trajectories, allowing users to influence the emotional outcomes based on their choices (Murray, 1997). This interactive narrative paradigm transforms storytelling into a participatory emotional experience. The emotional resonance of a narrative is inherently influenced by cultural nuances. Different cultures may respond to emotional arcs in distinct ways, shaping the narrative conventions and preferences within specific societies (Nell, 2008).

Understanding these cultural influences is crucial for creating emotionally impactful stories with global resonance. Crafting effective emotional arcs poses challenges for storytellers. Balancing predictability and surprise, avoiding clichés, and addressing the diverse emotional sensibilities of audiences are constant challenges (Keen, 2006).

Moreover, the ethical responsibility of storytellers to navigate sensitive topics with empathy and cultural awareness adds complexity to emotional storytelling. As storytelling evolves in the digital age, the landscape of emotional arcs undergoes further transformation. The integration of technology, artificial intelligence, and personalized narratives presents new opportunities and challenges in tailoring emotional experiences to individual preferences (Ryan, 2018). The future trajectories of emotional storytelling hint at a dynamic convergence of tradition and innovation.

In the dynamic landscape of the entertainment industry, understanding audience sentiments has become paramount for creators, marketers, and distributors. Sentiment analysis, also known as opinion mining, is a natural language processing technique that involves the extraction and analysis of sentiments, opinions, and emotions from textual data (Pang & Lee, 2008). In the context of the entertainment industry, sentiment analysis goes beyond textual reviews to decipher the emotional responses of audiences toward diverse content forms, including movies, TV shows, music, and online streaming. The application of sentiment analysis in the entertainment industry has evolved alongside advancements in computational linguistics and machine learning. From early rule-based systems to more sophisticated natural language processing algorithms, sentiment analysis has become a versatile tool for gauging audience reactions in real-time (Liu, 2015). The historical perspective traces the journey from simple sentiment polarity classification to nuanced emotion analysis.

The rise of social media platforms has turned them into a goldmine for sentiment analysis. Audiences express their opinions on movies, shows, and cultural phenomena on platforms like Twitter, Facebook, and Instagram. Sentiment analysis algorithms sift through this vast amount of user-generated content, providing insights into the immediate and unfiltered emotional responses of audiences (Ghiassi, Skinner, & Zimbra, 2013). Sentiment analysis has proven instrumental in predicting box office success. By analyzing sentiments expressed in pre-release discussions, trailers, and promotional materials, predictive models provide valuable forecasts regarding the potential success or challenges a movie might face (Asur & Huberman, 2010). This data-driven approach aids distributors and filmmakers in strategic decision-making.

Content creators leverage sentiment analysis to fine-tune their creative endeavors. By understanding audience reactions, content producers can adjust narrative elements, character arcs, and even marketing strategies to align with audience expectations (Joulin et al., 2017). This iterative process ensures that creative endeavors resonate emotionally with the target audience. Sentiment analysis plays a pivotal role in the personalization of content recommendations. Streaming platforms utilize sentiment insights to recommend movies or shows that align with users' emotional preferences (Wu, Aberer, & Datta, 2013). The result is a more personalized and engaging viewing experience, fostering audience loyalty. Despite its potential, sentiment analysis grapples with challenges and ethical considerations. Issues such as context ambiguity, cultural nuances, and the potential for algorithmic bias underscore the importance of responsible deployment (Kiritchenko et al., 2014). Ensuring that sentiment analysis enhances, rather than diminishes, the user experience requires ongoing attention.

The future of sentiment analysis in the entertainment industry lies in the integration of artificial intelligence (AI) for more nuanced emotional understanding. Advanced AI models, including deep learning architectures, hold the promise of deciphering complex emotional expressions, sarcasm, and cultural contexts, further enriching the insights derived from sentiment analysis (Cambria & White, 2014). In the era of digital content consumption, recommendation algorithms have become integral to platforms such as streaming services. These algorithms, powered by machine learning and data analytics, analyze user behaviors, preferences, and interactions to suggest content tailored to individual tastes (Adomavicius & Tuzhilin, 2005). The evolution of these algorithms marks a shift from generic suggestions to personalized content curation. Storytelling has always been a conduit for evoking emotions. Whether it's joy, suspense, or sorrow, narratives strive to connect with audiences on an emotional level (Brewer & Lichtenstein, 1982). The integration of emotional resonance within storytelling forms the foundation upon which personalized recommendation algorithms build. Recommendation algorithms extend their capabilities beyond genre preferences and viewing history to understand emotional preferences.

By employing sentiment analysis and emotion recognition techniques (Cambria et al., 2013), these algorithms decipher the emotional nuances within content and align them with users' predispositions, creating a more tailored and emotionally resonant viewing experience. The personalized emotional journey facilitated by recommendation algorithms leads to heightened user engagement. When users encounter content that not only aligns with their thematic preferences but also resonates emotionally, the likelihood of prolonged engagement and satisfaction increases (Hu et al., 2008). This user-centric approach transcends traditional content consumption patterns. The synergy between cognitive computing and affective computing plays a crucial role in refining personalized emotional journeys.

Recommendation algorithms, powered by cognitive systems, process vast datasets to understand narrative structures, character dynamics, and emotional arcs. Affective computing, on the other hand, decodes user emotions through facial expressions, physiological responses, and behavioral cues (Picard, 2003). The convergence of these technologies ensures a holistic approach to personalizing emotional narratives. As recommendation algorithms strive to personalize emotional experiences, ethical considerations come to the forefront. Balancing personalized recommendations with user privacy, avoiding algorithmic biases that may reinforce stereotypes, and ensuring transparency in the data-driven decision-making process pose ongoing challenges (Ekstrand et al., 2018). The responsible deployment of recommendation algorithms becomes imperative for maintaining trust and user satisfaction. Looking in the future of personalized emotional journeys lies in the integration of artificial intelligence (AI) for more sophisticated emotional storytelling. Advanced AI models, including deep learning architectures, hold the potential to comprehend and generate emotionally rich narratives that align seamlessly with individual preferences (LeCun et al., 2015). The convergence of AI-driven emotional storytelling and recommendation algorithms is poised to redefine the landscape of content consumption.

Emotions are complex, multifaceted phenomena that span a spectrum of nuances, from subtle micro expressions to profound emotional states (Ekman, 1992). The recognition and representation of these nuances in content creation require sophisticated tools, and deep learning emerges as a powerful paradigm for decoding the intricacies of emotional expressions. Deep learning, a subset of machine learning, employs neural networks with multiple layers (LeCun, Bengio, & Hinton, 2015). These architectures excel at learning hierarchical representations of data, making them adept at capturing the nuanced features inherent in emotional expressions. From convolutional neural networks (CNNs) for image analysis to recurrent neural networks (RNNs) for sequential data, deep learning models offer a versatile toolkit for understanding emotional complexity.

Deep learning plays a pivotal role in facial expression analysis, where nuanced emotions are encoded in micro expressions and subtle facial cues. Convolutional neural networks, trained on vast datasets of facial expressions, exhibit remarkable accuracy in recognizing and categorizing nuanced emotions (Mollahosseini, Chan, & Mahoor, 2017). This capability has profound implications for fields ranging from psychology to entertainment. Beyond visual expressions, deep learning extends its reach into the realm of voice and speech emotion recognition. Recurrent neural networks, equipped with long short-term memory (LSTM) units, demonstrate efficacy in capturing the subtle variations in tone, pitch, and cadence that convey nuanced emotional states in spoken language (Weninger, Eyben, Schuller, Mortillaro, & Scherer, 2013). In the cinematic landscape, the integration of deep learning algorithms enriches storytelling by decoding emotional depth.

Deep learning models analyze visual and auditory cues, allowing filmmakers to craft narratives that resonate emotionally. From sentiment-aware scene composition to emotion-driven soundtrack recommendations, deep learning algorithms contribute to the emotional tapestry of cinematic experiences. Deep learning extends its influence on artistic creation, where algorithms are trained to understand and reproduce nuanced emotional expressions. Generative models, such as variational autoencoders (VAEs) and generative adversarial networks (GANs), enable the generation of art that encapsulates the emotional essence of the human experience (Elgammal, Liu, & Elhoseiny, 2017). This intersection of technology and art offers new possibilities for creative expression.

While deep learning excels in capturing nuanced emotional expressions, challenges and ethical considerations arise. Issues of bias in training data, the interpretability of deep learning models, and the potential for amplifying stereotypes underscore the importance of responsible development and deployment (Holstein & Verhulst, 2019). Addressing these challenges ensures that the benefits of deep learning in emotional representation are harnessed ethically. Looking forward, the fusion of deep learning with emotional artificial intelligence (AI) opens avenues for interactive and emotionally responsive experiences. From emotionally intelligent virtual assistants to interactive narratives that adapt to user emotions, the future trajectories of deep learning promise a dynamic and emotionally resonant era in content creation.

Emotional analytics, a subset of analytics that focuses on the extraction and analysis of emotional data, provides businesses with valuable insights into customer sentiments, preferences, and behavior (Davenport & Harris, 2007). By leveraging advanced technologies such as artificial intelligence and machine learning, emotional analytics goes beyond traditional metrics, offering a nuanced understanding of the emotional landscape.

Businesses are increasingly adopting emotional analytics to optimize customer experiences. By analyzing customer interactions, feedback, and sentiments, companies gain a deeper understanding of the emotional journey's customers undertake (Verhoef, Lemon, Parasuraman, Roggeveen, Tsiros, & Schlesinger, 2009). This knowledge allows for the customization of products, services, and marketing strategies to align with customer emotions, ultimately enhancing overall satisfaction and loyalty.

Social media platforms have become a goldmine for emotional analytics. Businesses harness sentiment analysis algorithms to parse through vast amounts of social data, extracting valuable insights into public opinions and brand sentiments (Liu, 2012). This real-time emotional intelligence aids in proactive reputation management, strategic marketing campaigns, and agile decision-making.

Emotional analytics extends beyond customer-centric applications to human resource management. By monitoring employee sentiments and engagement levels, businesses gain insights into organizational culture, employee satisfaction, and potential areas for improvement (Barsade & Gibson, 2007). This holistic approach to workforce management contributes to higher productivity and employee well-being.

The integration of emotional analytics into marketing strategies enables personalized and emotionally resonant campaigns. By understanding individual customer emotions, businesses can tailor marketing messages, advertisements, and product recommendations to evoke specific emotional responses (Srinivasan, Anderson, & Ponnavolu, 2002). This personalized approach not only enhances customer engagement but also contributes to higher conversion rates. As businesses delve into emotional analytics, ethical considerations and privacy concerns come to the forefront. The responsible use of emotional data requires transparency, consent, and the establishment of ethical guidelines to protect customer privacy (Duhigg, 2012). Striking a balance between extracting valuable insights and respecting individual boundaries is essential for the sustainable adoption of emotional analytics. Emotional analytics aids businesses in optimizing operational processes through predictive analytics. By anticipating customer emotions and behavior, companies can streamline supply chain management, inventory control, and resource allocation (Gandomi & Haider, 2015).

This proactive approach contributes to operational efficiency and cost reduction. Looking ahead in the future trajectories of business models informed by emotional analytics involve the seamless integration of emotional intelligence across various business functions. From supply chain management to strategic decision-making, the holistic application of emotional insights promises to redefine how businesses operate in an increasingly emotion-aware marketplace.

2.4.1. Conclusion

In conclusion, the integration of emotional analytics into business models signifies a paradigm shift in how organizations understand and respond to customer and employee emotions. This literature review has explored the diverse applications of emotional analytics, from customer experience optimization to personalized marketing and operational efficiency. As businesses continue to embrace the emotional dimension, the trajectory of informed decision-making and sustainable success appears boundless. As technology continues to advance, the synergy between deep learning and emotional expression holds the promise of transforming how we perceive and interact with content across diverse mediums. The amalgamation of emotion-aware algorithms, cognitive computing, and affective computing marks a transformative era where narratives are tailored not just based on thematic preferences but on the emotional resonances that make storytelling a deeply personal and enriching endeavors technology continues to advance, the integration of AI promises a deeper and more nuanced understanding of audience sentiments, opening new frontiers for the emotional landscape of entertainment. As the industry navigates the intersection of creativity and computational power, it is crucial to navigate ethical considerations and ensure a harmonious collaboration between human creativity and AI innovation.

CHAPTER III:

METHODOLOGY

This chapter will give a detailed description of the techniques used in the current study. This chapter provides the workflow of the proposed research methodology including the design of the machine learning algorithms for improving the quality of product and driving innovation in the entertainment industry. This main objective of this thesis aims to analyze and understand emotional arcs and how their trajectories can guide screenwriters. Using artificial intelligence (AI) for emotional sentiment analysis can help filmmakers understand the emotional journey in movies, which can make their work more efficient. The research also plans to use these emotional arcs to inspire new products and services in the entertainment industry. More details about the research are discussed in the following sections.

3.1 Operationalization of Theoretical Constructs

Operationalization of the research concepts helps in understanding and quantifying abstract concepts, or theoretical constructs, to interpret and analyze the workflow of the process. In the context this research which is based on the emotional arc of movies and its impact on product and service innovation in the entertainment industry, the key theoretical constructs for operationalization are as follows:

- ***Emotional Arc of Movies:***

The emotional arc of movies refers to the dynamic progression of emotional experiences and responses elicited from viewers throughout the duration of a film. This theoretical aspect can be operationalized by measuring emotional intensity at different points in the movie using physiological responses such as facial expression analysis, sentiment, and emotional analysis. This can help to structure and identify key emotional turning points.

- ***Application of AI and ML:***

AI and ML are used for analyzing and predicting emotional patterns in movie content. Operationalization of these concepts can quantify the accuracy and effectiveness of these models in predicting emotional responses using different models.

- ***Product and Service Innovation:***

Product and service innovation are the most prominent concepts in the entertainment industry. These aspects allow the development and implementation of new and improved techniques that help in determining the emotional preferences of the audience. Both products and services can be operationalized by effectively analyzing new film formats, storytelling techniques, or interactive experiences influenced by emotional insights. In addition, it also helps in assessing the changes in marketing strategies, user interfaces, or viewing platforms driven by emotional data.

The operationalization of the above-mentioned theoretical constructs enables this research to provide an efficient tool for understanding the emotional arc of movies to bring more innovation in the film industry.

3.2 Research Design

This research employs both qualitative and quantitative analysis methods to analyze the emotional arc of movies and foster innovation in the entertainment industry.

From a qualitative analysis for analyzing the emotional arc of movies to bring innovation in the entertainment industry. Qualitative analysis helps in interpreting and obtaining valuable insights from non-numerical data, such as text, interviews, or observations which are suitable for sentiment analysis. In the context of this study on the emotional arc of movies and its impact on product and service innovation in the entertainment industry, qualitative analysis provides insights about the subjective experiences and perceptions of individuals. The qualitative analysis is used to find suitable answers for the research questions and objectives that the study aims to address. The analysis provides an overview of the qualitative data sources and methods used in the study, such as interviews, content analysis, or participant observations.

On the other hand, the research also involves a quantitative approach. It uses Artificial Intelligence (AI) for sentiment analysis, which involves processing text data into numerical data, a process known as quantification. This aspect of the study aims to quantify the understanding of emotional arcs by generating data about emotions and their corresponding scores. This data-driven approach allows for objective measurements and statistical analysis, providing a more structured understanding of the emotional arcs and their impact on the success of movies.

Together, the combination of qualitative and quantitative methods forms a mixed-methods research design. This design allows for a more comprehensive understanding of the research problem, leveraging the strengths of both qualitative insights and quantitative measurements. This approach can lead to more reliable and valid results, providing a stronger foundation for decision-making and strategy development in the entertainment industry.

3.3 Population and Sample

The population considered for this study comprises individuals who are interested in entertainment content, specifically movies, across various demographics, cultural backgrounds, and preferences. This encompasses moviegoers, streaming service subscribers, and individuals engaged in diverse modes of cinematic experience. Considering the diverse nature of the population, a purposive and diverse sample is selected to capture a representative range of perspectives. The sample includes individuals who regularly attend theaters for cinematic experiences, participants subscribed to popular streaming platforms, reflecting the growing trend of digital movie viewers. In addition, the population also includes industry professionals such as filmmakers, producers and other professionals within the entertainment industry who contribute to the creation and innovation of movie content. While selecting the population, it is ensured that the population represents across different age groups, genders, cultural backgrounds, and geographic locations to account for variations in emotional responses and preferences.

The data collected has a sample size of 3500 which covers original English movie subtitles. Unfortunately, sample size of converted subtitles from other languages was significantly lower in count which led us to exclude the same from our analysis. Hence our focus was dedicatedly on the 3,500 English movies for our sample size**.** For sampling the data, this research employs a stratified sampling method. This method is selected since it ensures representation from different demographics and user groups, the population is divided into strata, and samples are randomly selected from each stratum.

The objective of this sampling technique is to categorize the data into multiple subgroups which are adequately represented in the final sample. In the context of this research on the emotional arc of movies driving product and service innovation in the entertainment industry, the stratified sampling technique ensures representation from different demographics, user groups, or movie genre interests.

3.4 Participant Selection

The participants for the experimental analysis are selected based on various demographic factors such as age, gender, income level, and cultural background. The participants are stratified based on their movie interests, distinguishing between frequent moviegoers, streaming service subscribers, and those who engage in various genres of cinematic experiences. Within each stratum, the sampling method is employed to select participants. This could involve using random number generators, selecting each participant, or other randomization techniques to ensure representativeness. In addition, the participants are selected in such a way that they represent the diverse perspectives and experiences that are relevant to the research questions considered in this study. While selecting the participants the criteria was clearly outlined that individuals or entities must meet to be eligible for participation. All participants considered are above 18 years of age and include both men and women.

The participants considered in this research have diverse opinions about the movie genre and their interests about a particular movie vary from one participant to another. Based on their feedback, the positive, neutral, and negative sentiments of the user was analyzed and leveraging the sentiments, the emotional arc of the movies was analyzed. Further, the findings are interpreted by considering the unique characteristics and trends observed within each stratum. This allows for a more nuanced understanding of how different subgroups respond to the emotional arc of movies and how it influences the movie and service innovation in the entertainment industry.

3.5 Instrumentation

This section will discuss the instrumentation process used in the study. This research implements an NRC (National Research Council) Emotion Lexicon for obtaining the emotions from the data. The study employs a sentiment analysis-based approach using different techniques such as NRCLex, AFINN (Affective Norms for English Words), EMoBERTa, and VADER (Valence Aware Dictionary and sentiment Reasoner) tools.

3.7.1. Existing Techniques used for Sentiment and Emotion Analysis

This section discusses existing techniques used for sentiment and emotion analysis which are outlined as follows:

- ***AFINN (Affective Norms for English Words):***

The AFFIN is a lexicon that assigns a numeric score to English words based on their sentiment or emotional tone. The scores range from negative to positive, with negative scores indicating negative sentiment, positive scores indicating positive sentiment, and zero indicating a neutral sentiment. The lexicon is typically provided as a text file with words and their associated sentiment scores. The text is tokenized into individual words or tokens. This step is essential for matching words with their corresponding sentiment scores in the AFINN lexicon. For each word in the text, the sentiment score is determined in the AFINN lexicon, and the scores are computed to get an overall sentiment score for the entire text. The result is in terms of positive, negative, or neutral. Further, the sentiment score is analyzed to determine the overall sentiment of the text. Positive scores indicate a positive sentiment, negative scores indicate a negative sentiment, and scores close to zero suggest a neutral sentiment.

The advantages of the AFINN tool are that it is a simple and fast method for sentiment analysis. It assigns a pre-computed sentiment score to each word and calculates the overall sentiment score for a text based on these scores. However, the AFINN suffers from the drawback such as it focuses only on sentiment analysis and provides a single positive/negative score for a given text. It lacks the granularity of

NRCLex in terms of distinguishing between different emotions. In addition, the model might struggle with capturing nuances in emotional content beyond a binary positive/negative sentiment.

- ***EMoBERTa Model:***

The EMoBERTa model is an Emotion Recognition in Conversation with RoBERTa, has been widely used for sentiment analysis due to its ability to capture contextual information from both left and right contexts in a sequence. The EMoBERTa model is a powerful pre-trained language model. It can capture complex contextual information and understand the relationships between words in a sentence. The pre-trained EMoBERTa model is fine-tuned on a sentiment analysis task to achieve state-of-the-art results. The pre-trained BERT model is fine-tuned on a sentiment analysis dataset. This involves updating the weights of the model on the specific task of recognizing emotional arcs of the movies.

The advantages of EMoBERTa model are, that it can handle multiple languages and is not limited to English. However, the implementation of the model can be computationally intensive, requiring substantial resources for training and inference. Besides, these models often perform better with large amounts of diverse training data.

- ***VADER (Valence Aware Dictionary and sentiment Reasoner):***

VADER is a pre-built sentiment analysis tool specifically designed for social media text. It is included in the NLTK (Natural Language Toolkit) library in Python and is known for its effectiveness in handling short and informal texts commonly found in social media platforms. VADER is lexicon and rule-based, relying on a pre-constructed sentiment lexicon and a set of grammatical rules to analyze sentiment. The tool consists of a pre-built sentiment lexicon that includes words scored for their sentiment intensity.

Each word in the lexicon is assigned a polarity score (positive or negative) and an intensity score. VADER uses a set of rules to analyze sentiment in each text. It considers elements such as punctuation, capitalization, and degree modifiers to enhance its accuracy in sentiment analysis. The tool considers the intensity of sentiment in a text by considering the degree modifiers associated with sentiment-bearing words. This allows it to capture the strength of sentiment expressed. Using the VADER tool, sentiment polarity scores for each sentence is calculated, indicating whether it is positive, negative, or neutral. Additionally, it calculates a compound score, which represents the overall sentiment intensity of the entire text. In this way, this tool can be leveraged to accurately determine the emotional arc of the movies.

The advantage of this tool is that it quickly provides sentiment scores for text. The effectiveness of the tool is mainly due to its ability to consider the intensity and polarity of sentiments in its analysis. The drawback of this tool is that it is not as effective as AFINN, and VADER tool in terms of categorizing the emotions. In addition, rule-based approaches can struggle with sarcasm and contextual understanding.

- ***Proposed NRC Emotion Lexicon (NRCLex)***

Considering the drawback of existing techniques, this research proposes the adoption of NRC emotion lexicon for extracting emotions. The NRC is a widely used lexicon that associates words with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). NRCLex, a Python library, is built upon this lexicon and provides a way to analyze the emotion content of a given text. The steps involved in the implementation of the proposed NRCLex for understanding the emotional arc of the movies are as follows:

- ***Word Emotion Association:***

The NRC Emotion Lexicon contains a list of words along with their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). Each word is labeled with binary values indicating the presence or absence of these emotions or sentiments.

- ***Text Processing:*** While creating an NRCLex object with a text segment, the tool processes the text to identify individual words that helps in interpreting the emotional aspects of the movie viewers.
- ***Emotion Identification:*** For each word in the text, NRCLex finds its association with emotions based on the NRC Emotion Lexicon. If the word is present in the lexicon, the associated emotions are recorded.
- ***Emotion Frequency Calculation:*** Further, NRCLex computes the frequency of each emotion in the given text segment by tallying the occurrences of words associated with each emotion.

- ***Affect Frequencies:*** The affect frequencies attribute of NRCLex provides a dictionary with emotion categories as keys and their corresponding frequencies in the text segment as values.
- ***Sentiment Analysis:*** The lexicon also includes information about positive and negative sentiments. NRCLex provides the overall positive and negative sentiment scores for the given text.
- ***Customization:*** NRCLex allows for customization by excluding specific emotion categories or sentiments if desired. In the code, the 'positive' and 'negative' keys are excluded to focus on the eight basic emotions.

The selection of the tool for emotion analysis often depends on the specific use case, requirements, and characteristics of the data. The advantage of this tool is its fine-grained emotion analysis. NRCLex is known for providing fine-grained emotion analysis by categorizing text into eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, disgust) and two sentiments (positive and negative). It uses a lexicon-based approach, leveraging a manually curated lexicon that associates words with emotions. This approach can be beneficial for capturing nuanced emotional content. However, the performance of this tool is affected due to certain weaknesses. The NRCLex tool relies on the words present in its lexicon. If a word is not in the lexicon, its emotional content may not be accurately captured.

The main reasons for selecting the NRC Lexicon for our Model are, its fine-grained analysis which allows for a more nuanced understanding of the emotional content in comparison to models that provide binary sentiment scores. Besides, the lexicon-based approach enables the proposed work to leverage a manually curated lexicon associating words with emotions. This can be advantageous when dealing with specific domains or contexts where the lexicon reflects domain-specific emotional nuances. The lexicon-based approach makes NRCLex transparent and interpretable. Analysts can understand why a certain emotion is associated with a particular text segment based on the presence of specific words in the lexicon. NRCLex specifically targets emotion categories, distinguishing between different types of emotions. This can be crucial in applications were understanding specific emotions (e.g., joy, trust, surprise) is more important than just determining overall sentiment. NRCLex is designed for English text, and if the analysis primarily involves English-language content, it can be a strong choice. However, if there is a need for support for multiple languages, other models like multilingual BERT-based models can be combined with the NRCLex model.

NRCLex allows for customization by excluding specific emotion categories or sentiments. In the provided code snippet, the exclusion of 'positive' and 'negative' keys demonstrates the flexibility to focus on specific emotions. Depending on the application domain, NRCLex might be more adaptable. For instance, if the lexicon includes domain-specific terms relevant to the analysis, it can provide better insights compared to models trained on general-purpose datasets. NRCLex may be more resource-efficient compared to complex models like BERT-based ones, making it suitable for scenarios with resource constraints.

3.7.2. Proposed Workflow

The stages involved in the proposed workflow is shown in figure 1 and the steps involved are discussed in the below steps:

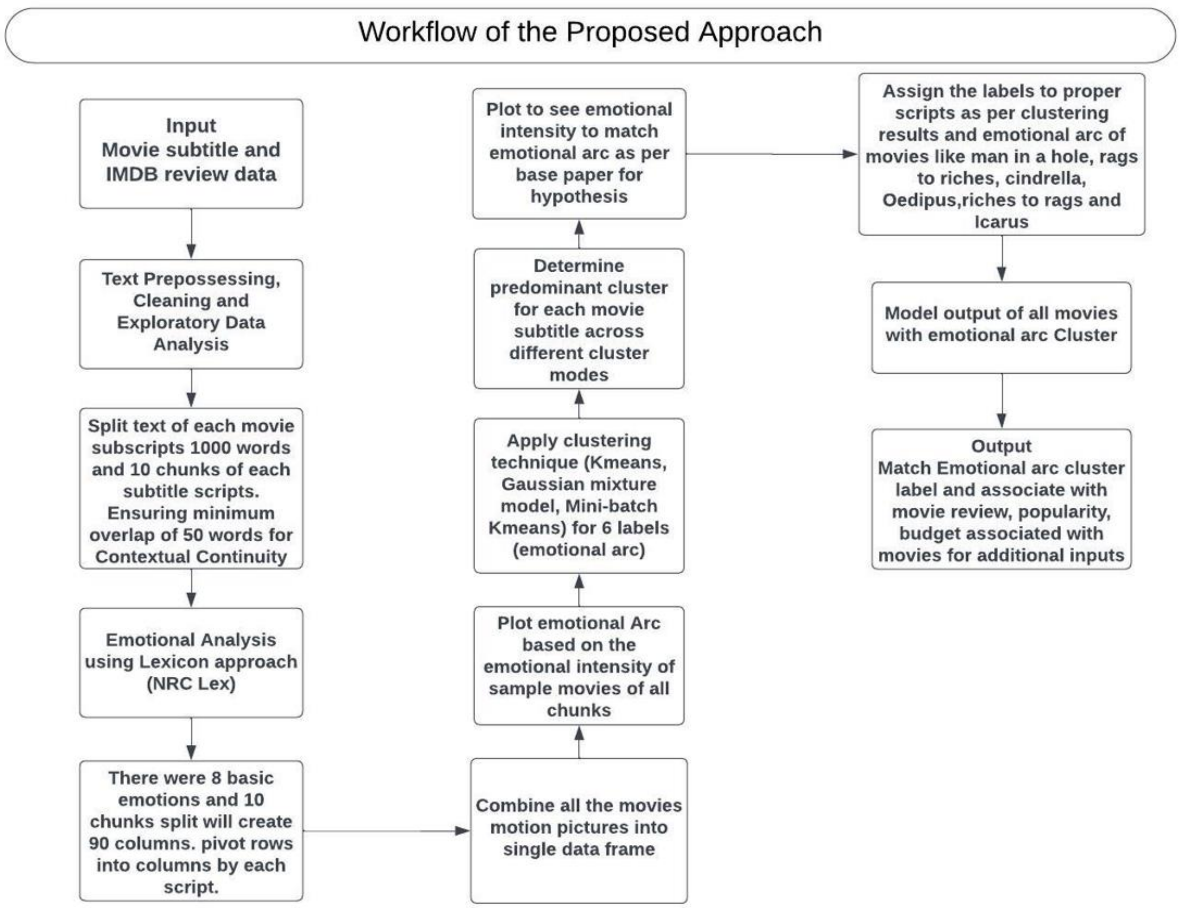


Figure 1 Workflow of the proposed approach

Step 1: Data collection and preprocessing

The links for assessing the dataset is provided below:

Movie details Link:
https://www.kaggle.com/datasets/adiamaan/movie-subtitle-dataset?select=movies_meta.csv

Movie subtitle link:

https://www.kaggle.com/datasets/adiamaan/movie-subtitle-dataset?select=movies_subtitles.csv

This section discusses the details of the dataset and the process for acquiring the same. In this research, the data for the experimental analysis is collected from the IMDB Kaggle dataset. In this step, the data from the movie dataset is collected for the analysis. Further, the data is subjected for preprocessing wherein the data is cleaned by removing the uncertainties such as special characters, spaces etc. The text or the subscript is split for every 1000 words and each movie is split based on the start and end time associated with it. The overlap of minimum 50 minutes such that no context is missed.

Step 2: Word Embedding

Word embeddings represent words as dense vectors in a continuous vector space, capturing semantic relationships between words based on their contextual usage. In this research, different types of word embedding techniques are employed such as Word2Vec and GloVe, POS2Vec (P2V) spacy, Lexicon2Vec (L2V), NRC emotions, sentiment embedding from LLM, and sentence transformers (embedding).

Step 3: Multi Model Evaluation

Different models such as NRCLex, AFINN, EMoBERTa, and VADER are implemented and tested in terms of identifying the emotional arch based on each word and sentiment score. In addition, the intensity of the sentiment such as joy, happiness, anger etc. are also considered for the analysis. Further, the intensity of the score is matched to the emotional arc and each movie is assigned with an appropriate label based on the emotional arc.

3.6 Data Collection Procedures

The process involved in the collection of data for experimental purposes are discussed in this research.

After collecting the data, preprocessing is performed to remove duplicate features and unwanted features. In this stage, both movie details and subtitles based on movie ID are combined to obtain an aggregated form.

3.7 Data Analysis

The data obtained from the dataset is analyzed using an Exploratory Data Analysis (EDA) technique. EDA is a crucial phase in the data analysis process where the data is explored and understood before applying more complex statistical or machine learning techniques.

EDA helps to uncover patterns, relationships, anomalies, and insights that inform subsequent analysis. The process of EDA is initiated by loading the dataset and obtaining a high-level overview. Further, the dimensions (number of rows and columns) of the dataset are checked and verified and the first few rows are displayed to understand the structure and types of data. The summary of the data analysis is generated to understand the central tendency, dispersion, and distribution of numerical variables. The data is thoroughly checked for the presence of missing values in the dataset. After identifying the missing values (if any) the data preprocessing is performed to handle missing data appropriately. The data types of each column are examined, and it is ensured that all data types are correctly interpreted (e.g., dates as datetime objects, categorical variables as categories). Explore unique values and frequency counts for categorical variables. After interpreting, the data distributions and relationships are visualized using various plots, such as histograms, box plots, scatter plots, and pair plots. Based on the analysis, the distribution of movies released in the top 10 years based on their frequency is plotted as shown in figure 2.

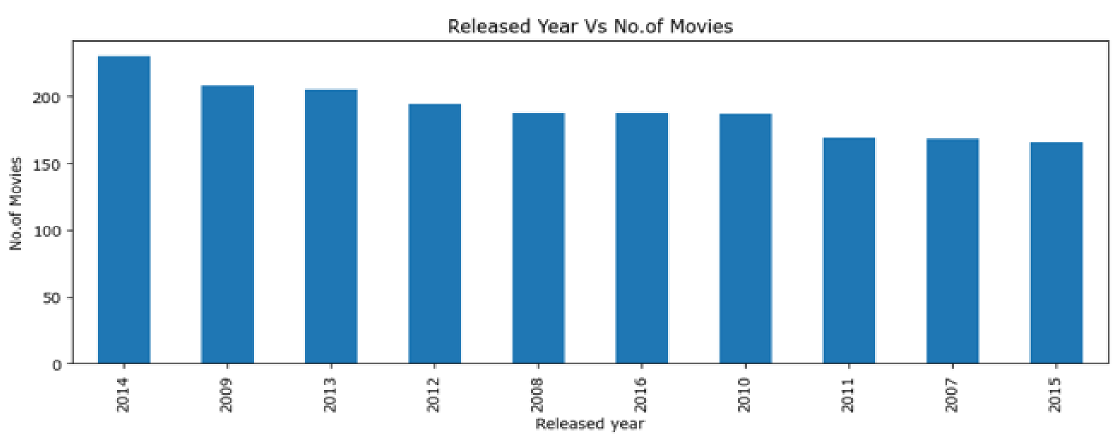


Figure 2 Distribution of movies released in the top 10 years.

In the second stage of the analysis, the plot displaying the top 10 movies with the highest runtime and their respective runtime values is visualized as shown in figure 3.

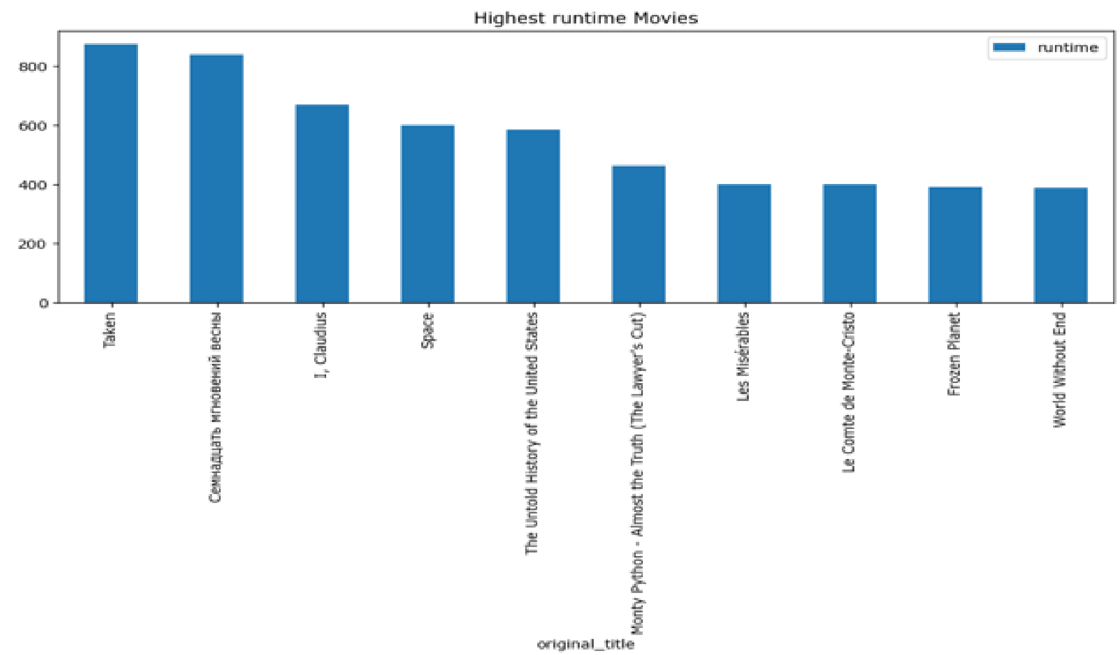


Figure 3 Plot visualizing top 10 movies with the highest runtime and their respective runtime values

The top 10 most profitable movies are illustrated in figure 4.

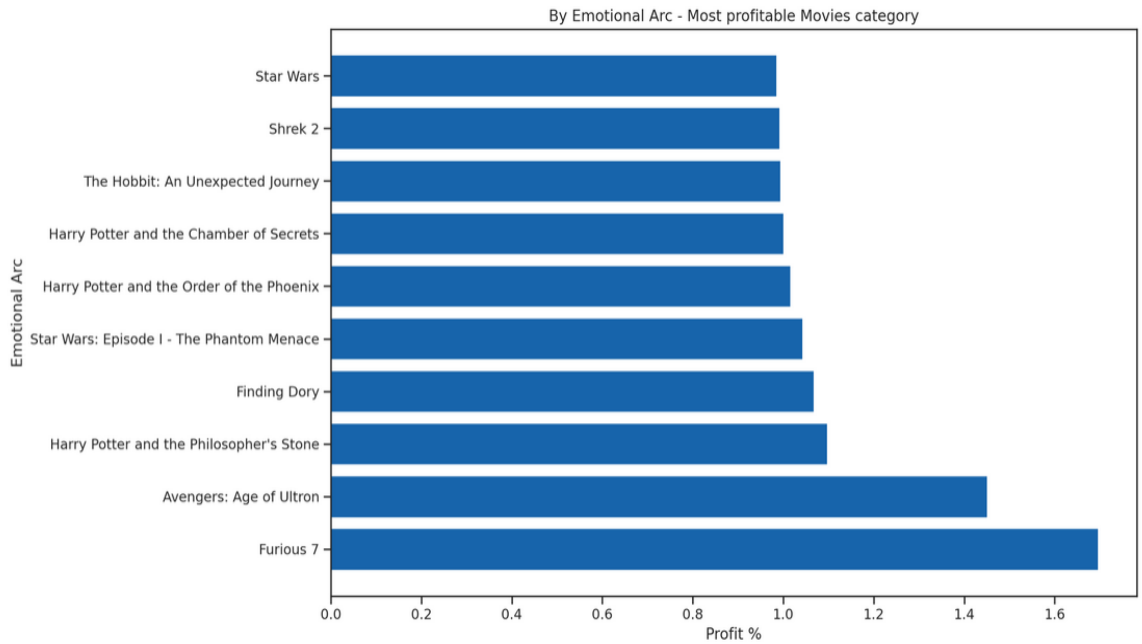


Figure 4 Most profitable movies

After visualizing the distribution of movies with respect to different aspects, the average vote of all movies is considered, which is shown in figure 6.

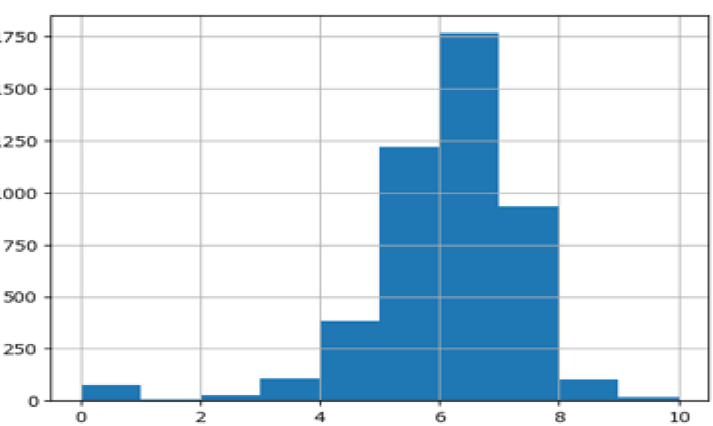


Figure 5 Average vote of all movies

A text chunking function known as split_subscript_with_time which takes a text, splits it into chunks of a specified size with an overlap, and assigns time intervals to each chunk. Size of each chunk is defined using the size_chunk function and the overlapping size between the chunks is determined using an overlap function. A specific time duration is assigned to each chunk and a list of dictionaries containing the chunk, start time, and end time is returned.

The split_subscript_with_time function is used to split the text into chunks, each with a maximum size of 1000 characters, an overlap of 25 characters, and a time step of 30. For each chunk, the start and end times are extracted, and the chunks along with their time information are stored in separate lists. Using this, the emotion counts for each chunk are extracted. For each text chunk, an NRCLex object is created using the NRCLex(segment) instantiation. The NRCLex then processes the text chunk and uses the NRC Emotion Lexicon to identify and count the occurrences of words associated with each emotion category (anger, fear, anticipation, trust, surprise, sadness, joy, disgust, negative, and positive). The affect frequencies attribute of the NRCLex object is then used to retrieve a dictionary of emotion counts for the given text chunk.

The dictionary includes the frequencies of words associated with each emotion category. The emotion counts for each chunk are collected and stored in the emotion_counts_all lists. This list will contain dictionaries where keys are emotion categories, and values are the corresponding frequencies in each chunk. The code defines a function `exclude_keys(emotion_count) ` to exclude the 'positive' and 'negative' keys from the emotion count dictionary. This step is performed to focus on the eight basic emotions rather than sentiments. For each chunk, a DataFrame is created from the emotion counts using pandas. The DataFrames are transposed, and column names are modified to include the chunk number. All the DataFrames created in the previous step are concatenated along the columns to form a single DataFrame (`final_df`) for a set of chunks. This process is repeated for all sets of chunks, and the resulting DataFrames are stored in the `final_df1` list. All DataFrames in the `final_df1` list are concatenated along the rows to form a single DataFrame (`result_df`). The index of the resulting DataFrame is then reset to ensure consecutive row indices.

3.8 Research Design Limitations

The limitations of this study are as follows:

- The limited sample size considered in this study can impact the generalizability of findings to a broader population. Small samples may not adequately represent diverse groups or contexts. Subtitles from languages such as French, Japanese, Italian, and Hindi were excluded from the analysis due to their low volume.

- Only movie subtitles associated with IMDb ratings were considered for this analysis, while those unavailable were excluded which may impact the overall recommendation.

3.9 Conclusion

This research focuses on accurately understanding and interpreting the emotional arc of the movies to drive product and service innovation in the entertainment industry. The proposed work discusses the application of different tools such as NRCLex, AFINN, EMoBERTa, and VADER for capturing the sentiment of the movie users. After validating different tools, this research considers the implementation of the NRCLex tool because of its effectiveness in terms of achieving fine grained analysis and interpreting complex data patterns. This aspect helps in understanding the emotions of the users for different movie genres which is visualized using EDA. The implementation of the NRCLex tool can be considered as a potential tool to drive the product and motivate movie makers to bring innovation in the entertainment industry and thereby enhance the overall customer experience.

CHAPTER IV:

RESULTS

4.1 Research Question One

- Research Question #1(RQ1):

How can the integration of Artificial Intelligence models, computational narratology, and Natural Language Processing (NLP) revolutionize the conventional comprehension of emotional arcs, aiding businesses in identifying the most financially successful emotional arc categories.?

Dataset Extraction:

To date, our research has shown that the Man in a Hole emotional trajectory produces the highest overweight local revenue, which supports our prediction 2 in part. Additionally, we discovered that this emotional trajectory is the highest earning because, based on the supposition that IMDb ratings do, in fact, capture viewer satisfaction rates, rather than because it generates the most "liked" content. Instead, films in this cluster garner the most attention from viewers (De Pater, Judge and Scott, 2014; Hwangbo and Kim, 2019). We will now examine whether and how production budgets impact revenues as we move on to the robustness check of our findings. Movies are costly to make, so it's critical to know if and how much high earnings are correlated with the amount of initial investment made in the film's creation (Kim, Kang and Jeong, 2018a; Zhou, Zhang and Yi, 2019b). We examine the estimated production budgets for a subsample of our dataset that we obtained from the com repository to investigate this problem.

- **Data preprocessing & Exploratory Data Analysis:**

Once the dataset has been extracted, redundant and unwanted features must be eliminated. Following that, we used text preprocessing to clean the subtitles for every movie.

- **Text Chunking Function**

split_subscript_with_time: This function takes a text, splits it into chunks of a specified size with an overlap, and assigns time intervals to each chunk.

chunk_size: Size of each chunk.

overlap: Overlapping size between chunks.

time_step: Time duration assigned to each chunk. It returns a list of dictionaries containing the chunk, start time, and end time.

1. **Splitting Text into Chunks and Extracting Time Information:**

- The split_subscript_with_time function is used to split the text into chunks, each with a maximum size of 1000 characters, an overlap of 25 characters, and a time step of 30.
- For each chunk, the start and end times are extracted, and the chunks along with their time information are stored in separate lists.

2. **Extracting Emotion Counts for Each Chunk:**

- For each text chunk, an NRCLex object is created using the ***NRCLex(segment)*** instantiation.
- NRCLex then processes the text chunk and uses the NRC Emotion Lexicon to identify and count the occurrences of words associated with each emotion category (anger, fear, anticipation, trust, surprise, sadness, joy, disgust, negative, and positive).
- The affect_frequencies attribute of the NRCLex object is then used to retrieve a dictionary of emotion counts for the given text chunk. The dictionary includes the frequencies of words associated with each emotion category.
- The emotion counts for each chunk are collected and stored in the emotion_counts_all lists. This list will contain dictionaries where keys are emotion categories, and values are the corresponding frequencies in each chunk.
- The code defines a function `exclude_keys(emotion_count) ` to exclude the 'positive' and 'negative' keys from the emotion count dictionary. This step is performed to focus on the eight basic emotions rather than sentiments.

3. **Creating DataFrames for Emotion Counts:**

The code defines a function `exclude_keys` to exclude the 'positive' and 'negative' keys from the emotion count dictionary. For each chunk, a DataFrame is created from the emotion counts using pandas. The DataFrames are transposed, and column names are modified to include the chunk number.

4. **Concatenating DataFrames:**

All the DataFrames created in the previous step are concatenated along the columns to form a single DataFrame (`final_df`) for a set of chunks. This process is repeated for all sets of chunks, and the resulting DataFrames are stored in the `final_df1` list.

5. **Concatenating Final DataFrames:**

All DataFrames in the `final_df1` list are concatenated along the rows to form a single DataFrame (`result_df`). The index of the resulting DataFrame is then reset to ensure consecutive row indices.

4.2 Research Question Two

- Research Question #2 (RQ2):

How effective are computational sentiment analysis tools such as NRCLex, AFINN, EMoBERTa, and VADER in providing data-driven emotional insights that not only enhance the understanding of emotional arcs in motion pictures but also empower filmmakers to make informed decisions?

The NRC (National Research Council) Emotion Lexicon is a widely used lexicon that associates words with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). NRCLex, a Python library, is built upon this lexicon and provides a way to analyze the emotion content of a given text.

1. **Word Emotion Association:**

The NRC Emotion Lexicon contains a list of words along with their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). Each word is labeled with binary values indicating the presence or absence of these emotions or sentiments.

2. **Text Processing:**

When you create an NRCLex object with a text segment, NRCLex processes the text to identify individual words.

3. **Emotion Identification:**

For each word in the text, NRCLex checks its association with emotions based on the NRC Emotion Lexicon. If the word is present in the lexicon, the associated emotions are recorded.

4. **Emotion Frequency Calculation:**

NRCLex computes the frequency of each emotion in the given text segment by tallying the occurrences of words associated with each emotion.

5. **Affect Frequencies:**

The affect_frequencies attribute of NRCLex provides a dictionary with emotion categories as keys and their corresponding frequencies in the text segment as values.

6. **Sentiment Analysis:**

The lexicon also includes information about positive and negative sentiments. NRCLex can provide the overall positive and negative sentiment scores for the given text.

7. **Customization:**

NRCLex allows for customization by excluding specific emotion categories or sentiments if desired. In the code, the 'positive' and 'negative' keys are excluded to focus on the eight basic emotions. NRCLex, AFINN, EMoBERTa, and VADER are different tools and libraries for sentiment and emotion analysis, each with its own strengths and weaknesses. The choice between them often depends on the specific use case, requirements, and characteristics of the data.

- **NRCLex:**

Strengths:

Fine-grained Emotion Analysis: NRCLex is known for providing fine-grained emotion analysis by categorizing text into eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, disgust) and two sentiments (positive and negative).

Lexicon-based Approach: It uses a lexicon-based approach, leveraging a manually curated lexicon that associates words with emotions. This approach can be beneficial for capturing nuanced emotional content.

Weaknesses:

Limited to Lexicon Entries: NRCLex relies on the words present in its lexicon. If a word is not in the lexicon, its emotional content may not be accurately captured.

- **AFINN (Affective Norms for English Words):**

Strengths:

Simple and Fast: AFINN is a simple and fast method for sentiment analysis. It assigns a pre-computed sentiment score to each word and calculates the overall sentiment score for a text based on these scores.

Weaknesses:

Limited Emotion Categories: AFINN primarily focuses on sentiment analysis and provides a single positive/negative score for a given text. It lacks the granularity of NRCLex in terms of distinguishing between different emotions. The model may struggle with capturing nuances in emotional content beyond a binary positive/negative sentiment.

- **EMoBERTa:**

Strengths:

BERT-based Model: EMoBERTa is based on BERT (Bidirectional Encoder Representations from Transformers), a powerful pre-trained language model. It can capture complex contextual information and understand the relationships between words in a sentence. BERT-based models like EMoBERTa can handle multiple languages and are not limited to English.

Weaknesses:

Computational Intensity: BERT-based models, including EMoBERTa, can be computationally intensive, requiring substantial resources for training and inference.
Need for Large Amounts of Data: These models often perform better with large amounts of diverse training data.

- **VADER (Valence Aware Dictionary and sentiment Reasoner):**

Strengths:

Rule-based and Fast: VADER is a rule-based sentiment analysis tool that quickly provides sentiment scores for text.
Handles Intensity and Polarity: It considers the intensity and polarity of sentiments in its analysis.

Weaknesses:

*Limited Emotion Categories***:** Like AFINN, VADER focuses more on sentiment analysis and provides a compound sentiment score, which may not be as detailed as NRCLex' s emotion categories.
Challenges with Sarcasm and Context: Rule-based approaches can struggle with sarcasm and contextual understanding.

Considerations for Choosing NRC Lexicon for our Model:

- **Fine-Grained Emotion Analysis:**

NRCLex provides a fine-grained analysis by categorizing text into eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, disgust) and two sentiments (positive and negative). This granularity allows for a more nuanced understanding of the emotional content in comparison to models that provide binary sentiment scores.

- **Lexicon-Based Approach:**

NRCLex adopts a lexicon-based approach, leveraging a manually curated lexicon associating words with emotions. This can be advantageous when dealing with specific domains or contexts where the lexicon reflects domain-specific emotional nuances.

- **Transparency and Interpretability:**

The lexicon-based approach makes NRCLex transparent and interpretable. Analysts can understand why a certain emotion is associated with a particular text segment based on the presence of specific words in the lexicon.

- **Specific Emotion Categories:**

NRCLex specifically targets emotion categories, distinguishing between different types of emotions. This can be crucial in applications were understanding specific emotions (e.g., joy, trust, surprise) is more important than just determining overall sentiment.

- **Non-English Language Support:**

NRCLex is designed for English text, and if our analysis primarily involves English-language content, it can be a strong choice. However, if I need support for multiple languages, you may need to consider other models like multilingual BERT-based models.

- **Customization Options:**

NRCLex allows for customization by excluding specific emotion categories or sentiments. In the provided code snippet, the exclusion of 'positive' and 'negative' keys demonstrates the flexibility to focus on specific emotions.

- **Domain Adaptability:**

Depending on the application domain, NRCLex might be more adaptable. For instance, if the lexicon includes domain-specific terms relevant to our analysis, it can provide better insights compared to models trained on general-purpose datasets.

- **Resource Efficiency:**

NRCLex may be more resource-efficient compared to complex models like BERT-based ones, making it suitable for scenarios with resource constraints.

Apply K-means, Mini Batch K-means, and Gaussian Mixture clustering for clustering the emotional Arcs:

Here we applied different clustering technique for clustering the features.

- **KMeans Clustering:**

KMeans is a popular clustering algorithm that partitions data points into 'k' clusters based on their features. The algorithm iteratively assigns each data point to the nearest cluster centroid and updates the centroids until convergence. The **k-means++** initialization method is commonly used, which intelligently selects initial cluster centroids to speed up convergence. KMeans is sensitive to the initial placement of cluster centroids and may converge to a local minimum, so it's often recommended to run the algorithm multiple times with different initializations (`n_init`) and select the best result.

- **Gaussian Mixture Model (GMM) Clustering:**

GMM assumes that the data points are generated from a mixture of several Gaussian distributions, each associated with a different cluster. Unlike KMeans, which assigns each data point to only one cluster, GMM calculates the probability that each data point belongs to each cluster. GMM iteratively updates the parameters of the Gaussian distributions to maximize the likelihood of the observed data. It can model clusters with different sizes and shapes and is robust to noisy data. Here we applied the clustering method for our features for clustering and here we combine Gaussian Mixture cluster feature into the DataFrame.

- **Mini-Batch KMeans Clustering:**

Mini-Batch KMeans is a variation of the KMeans algorithm designed to handle large datasets more efficiently. Instead of using the entire dataset to update cluster centroids in each iteration, Mini-Batch KMeans randomly selects a subset (mini-batch) of the data. It updates cluster centroids based on this mini batch, which accelerates the convergence process and reduces memory usage. Mini-Batch KMeans is particularly useful for datasets that don't fit into memory and when computational resources are limited. However, it may produce slightly different results compared to standard KMeans due to the use of mini batches.

Assigning Final Cluster Labels:

- A DataFrame result_df1 is created containing only the cluster labels from 'GaussianMixture_cluster', 'kmeans_cluster', and 'minibatch_kmeans_cluster'.
- Combine output of all 3 cluster and create a pattern.

  final_df['pattern'] = (final_df['kmeans_cluster'].astype(str) +

  final_df['GaussianMixture_cluster'].astype(str) +

  final_df['minibatch_kmeans_cluster'].astype(str))
- The resulting patter is used to pass to Custom Pattern Combination Selection Methodology to associate each pattern values assigned as the final cluster labels and added to final_df as a new column named 'Emotiona_arc_label.'
- After this, we need to know which combination of patter are associated to emotional arc (Rags to riches, Riches to Rags, Cinderella etc..) by referring sample movies

identified by previous research paper and based on the result , we finalize the cluster with emotional arc.

- After this, we evaluate our model into those movies and compute the cluster values which belongs to which emotional arc.
- Here we compute the cluster with emotional arc which has maximum clustering values for the emotional arc.
- After evaluating all movie text (12 movies), we finalized these are the clustering values (Maximum occurred) which belongs to this emotional arc.

4.3 Summary of Findings

Intelligent feedback can be generated in interactive multimedia stories through artificial intelligence and machine learning processing, which can also be used to personalize the narrative's overall structure, make it more emotionally relevant to the reader, and give the reader a deeper sense of belonging (Jain, 2013; Kasunic and Kaufman, 2018b; Kim, Kang and Jeong, 2018a; Zhou, Zhang and Yi, 2019b). We discovered that learners favor a serious story's emotional arc of "rise-fall-rise" based on the findings. As a result of this emotional journey.

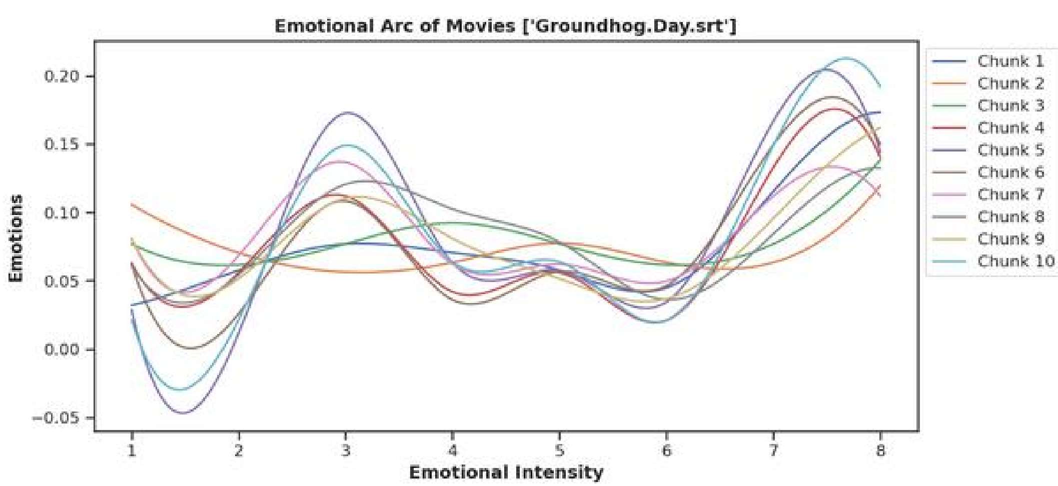
A comparison of the average like rates of the six distinct types of serious reports revealed that the Cinderella cluster was the most popular, outperforming serious narratives influenced by other emotional arcs. This emotional arc's primary characteristic, is its ups and downs in the middle of the story with a definite emotional rise at the end. Additionally, the plot's negative feeling (b2) at the middle is lower than its negative value at the beginning, and its positive value at the end is higher than its positive value in the development process story. Furthermore, the negative feelings of plot emotions in the middle of the story are lower than the negative value at the beginning of the story, and the positive value at the end of the narrative is higher than the positive value in the development process story. By analyzing these six arcs and their readers' preferences, in general, "Man in a Hole "and "Cinderella" emotional arcs, which have a good ending after the story's tortuous development, have higher preferences. In contrast, fewer readers prefer "Rags to Riches," with rising emotions without twists and turns. These narratives adhere to the "fall" emotional arc while also having the power to persuade readers to fulfill the educational goal (Nic Theo, 2016). Three categories of serious narratives conclude in tragedy: the serious narratives "Oedipus" and "Riches to Rags" both begin and end in a sad emotional state, while the narrative "Icarus" begins and ends in a sad emotional state. When comparing these three emotional arc types, users are more inclined to favor the "Oedipus" and "Riches to Rags" emotional arcs than the "Icarus".

The audience that provides the IMDb ratings is not the same as the one that largely funds the film, etc. Additional variables that reflect the quantity of people rating and reviewing content on IMDb offer more context for understanding the discrepancy between ratings and gross domestic revenue. The Man in a Hole emotional trajectory has a positive and significant correlation with all three of the IMDb variables that measure activity levels: rating count, user reviews, and critic reviews. If the average IMDb user rating and the IMDb meta score are interpreted as proxies for the satisfaction of viewers and critics, respectively, our findings may indicate that the most popular films are not always the ones that the public enjoys, but rather the ones that garner the greatest attention.

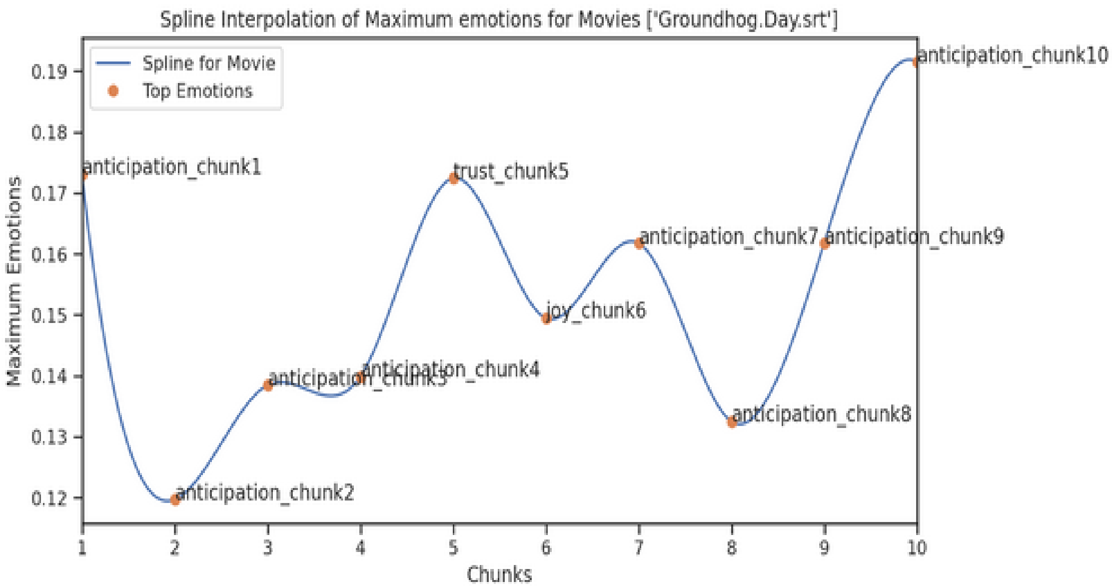
Emotional Arc of Rags to Riches - Rise

- **Movie - Groundhog Day**

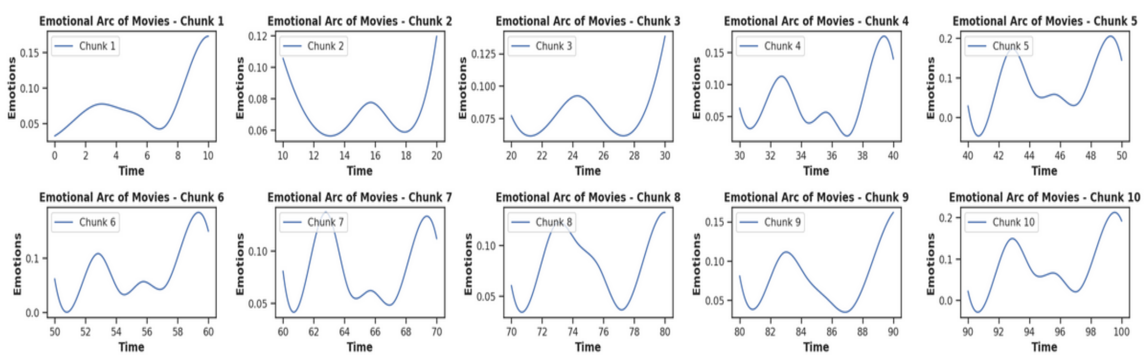
It's interesting to note that there is a statistically significant negative correlation between the Riches to Rags cluster. The impact is noteworthy; according to Figure 6a and 6c, chunk 1 (the start chunk) and chunk 10 (the final chunk) indicate the emotional intensity Rise moment, which denotes the Emotional arc of Rags to Riches. The emotional flow of Groundhog Day is depicted in Figure 6b, where the positive Top emotion intensity begins with anticipation (at lower intensity 0.07(7%)) and ends with anticipation at high positive intensity around 0.19 (19%)). Positive feelings such as trust, anticipation, and joy are evident in all ten sections as a Top Emotions of the movie text.



a



b

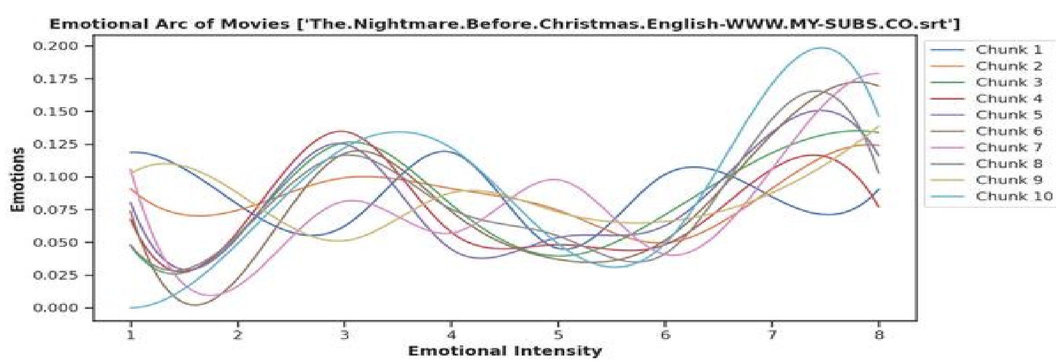


c

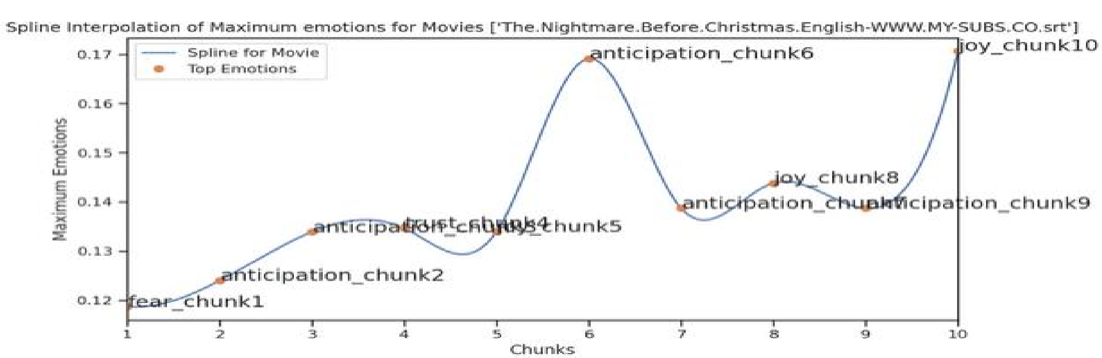
Figure 6 Emotional Arc of Rags to Riches - Rise Rise Rise Top Emotions in Groundhog Day

- **Movie – A Night Before Christmas (1993):**

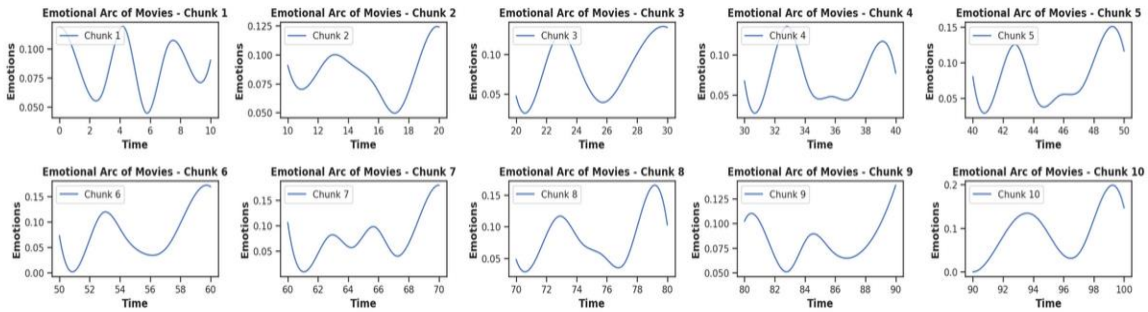
It's interesting to note that there is a statistically significant negative correlation between the Riches to Rags cluster and follows similar pattern with Ground hog day movie. The impact is noteworthy; according to Figure 7a and 7c, chunk 1 (the start chunk) and chunk 10 (the final chunk) indicate the emotional intensity Rise moment, which denotes the Emotional arc of Rags to Riches. The emotional flow of Night Before Christmas is depicted in Figure 7b, where the Negative emotion intensity begins at Fear (0.11(11%) and spikes towards end with anticipation (0.18 (18%)). While Movie story line progress with Positive emotions and ends with high positive emotion.



a



b



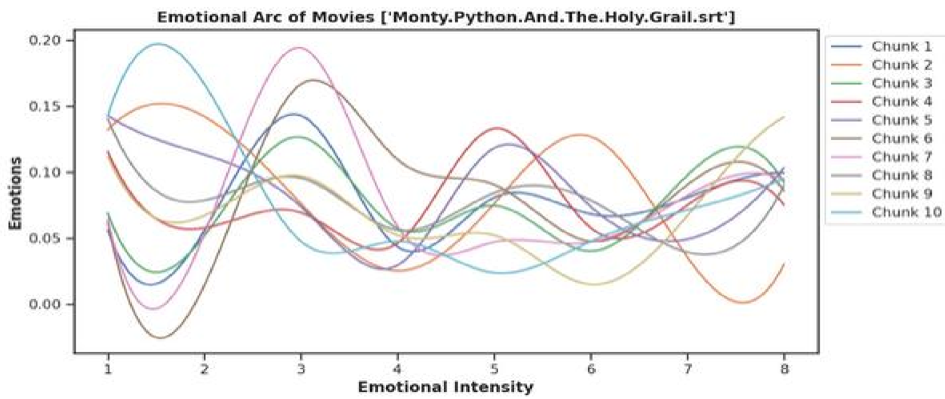
C

Figure 7 Emotional Arc of Rags to Riches - Rise - Top Emotions in The Night before Christmas

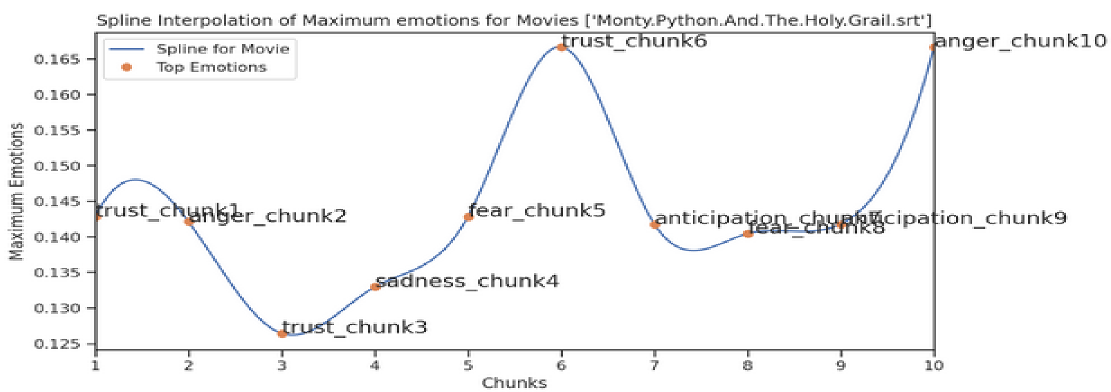
Emotional Arc of Riches to Rags- Fall

- **Movie -Monty Python and The Holy Grail**

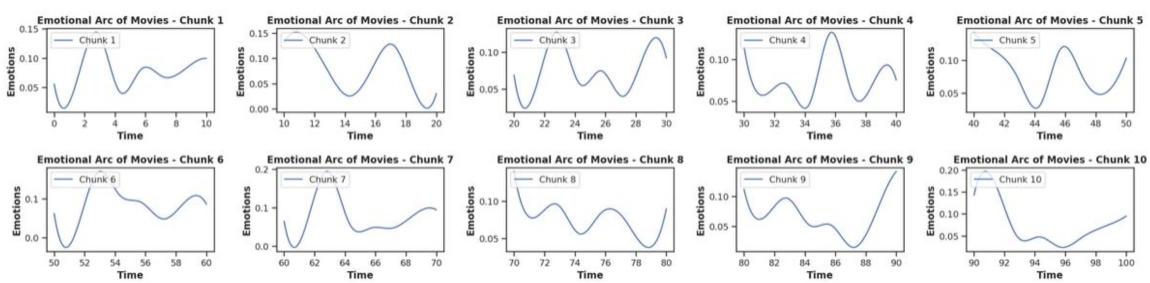
It's interesting to note that there is a statistically significant negative correlation between the Rags to Riches cluster. The impact is noteworthy, according to Figure. 8a and 8c, chunk 1 (the start chunk) and chunk 10 (the final chunk) indicate the emotional intensity Fall moment, which denotes the Emotional arc of Riches to Rags. The emotional flow of Monty Python and The Holy Grail is depicted in Figure 8b, where flow starts with positive emotion intensity begins at Trust (0.143(14%) and spikes towards negative Emotion intensity end with Anger (0.16 (16%)). While Movie story line progress with low Positive emotions and ends with high negative emotion.



a



b



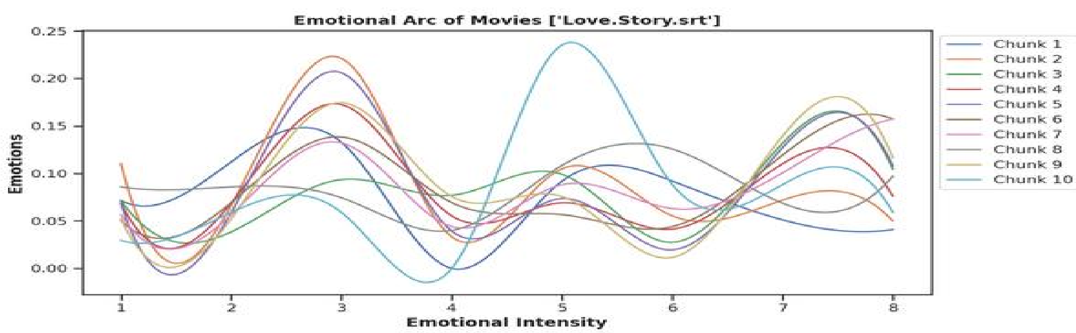
c

Figure 8 Emotional Arc of Riches to Rags- Fall Monty Python and the Holy Grail

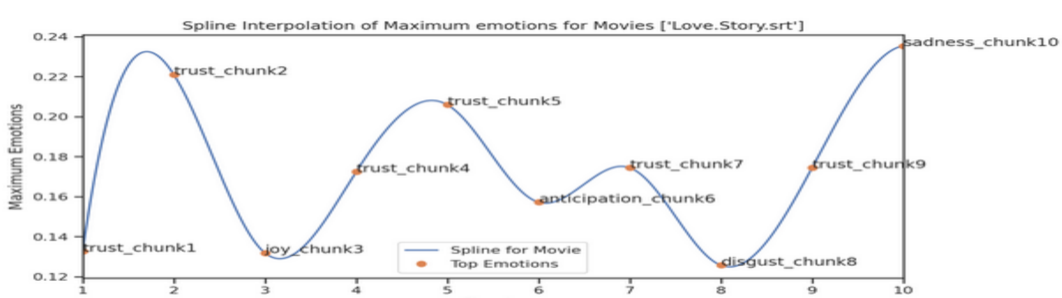
Movie -Love story:

It's interesting to note that there is a statistically significant negative correlation between the Rags to Riches cluster. The impact is noteworthy; according to Figure 9a and 9c, chunk 1 (the start chunk) and chunk 10 (the final chunk) indicate the emotional intensity Fall moment, which denotes the Emotional arc of Riches to Rags. The emotional flow of Love story is depicted in Figure 9b, where flow starts with Low positive emotion intensity begins at Trust (0.13(13%) and spikes towards high negative Emotion intensity end with sadness (0.23 (23%)). While Movie story line progress with low Positive emotions and ends with high negative emotion.

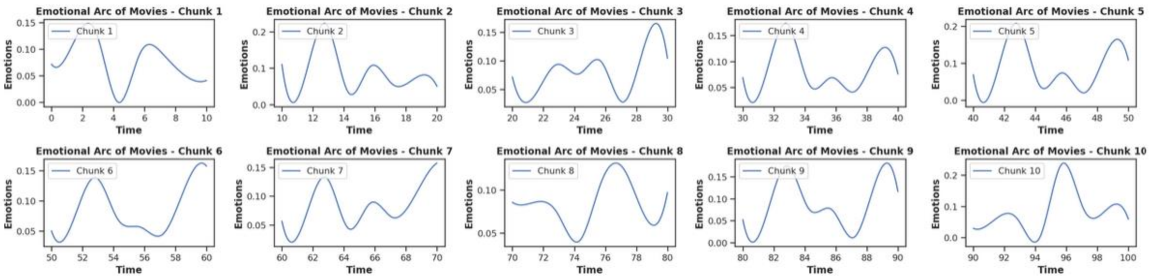
.



a



b



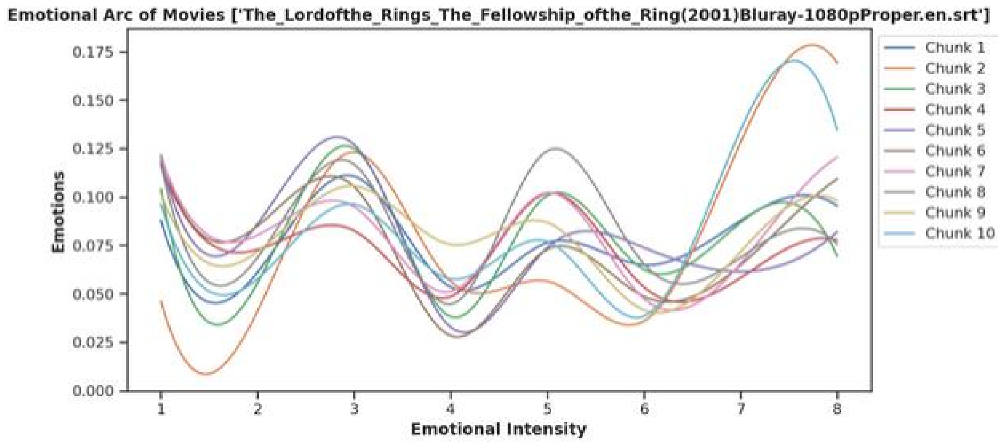
C

Figure 9 Emotional Arc of Riches to Rags- Love story

Emotional Arc of Man in Hole - Fall-Rise

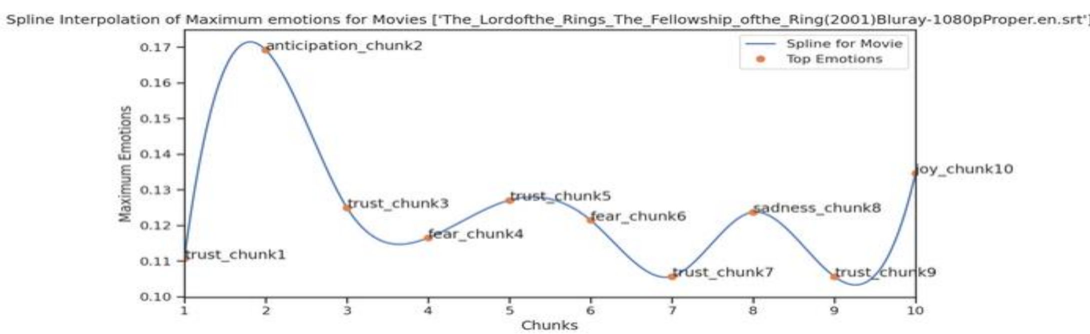
- **Movie -Lords of Rings:**

It's interesting to note that there is a statistically significant negative correlation between the Icarus cluster. The impact is noteworthy; according to Figure 10a and 10c, chunk 1 (the start chunk) and chunk 10 (the final chunk) indicate the emotional intensity Intial Fall and Raise moment, which denotes the Emotional arc of Man in a hole. The emotional flow of Lord of the Rings is depicted in Figure 10b, where flow starts with positive emotion intensity begins at Trust (0.11 (11%)) & high positive Anticipation (positive) (0.17(17%) and steep Fall towards emotion intensity of Fear (0.11(11%)) and end with Joy (positive emotion (0.14 (14%)). While Movie story line progress with high Positive emotions and Unexpected Fall in between and ends story line with positive emotion.

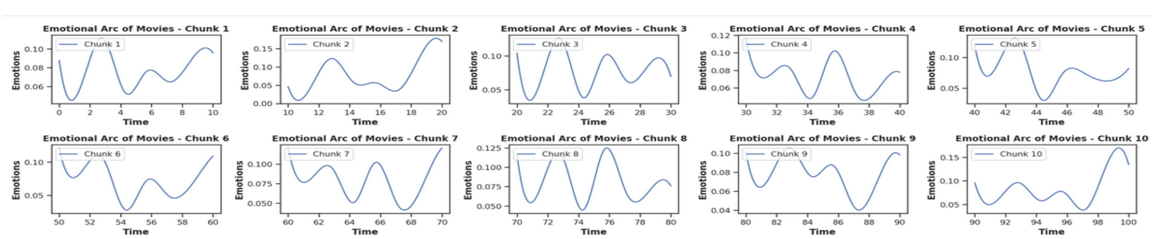


.

a



b

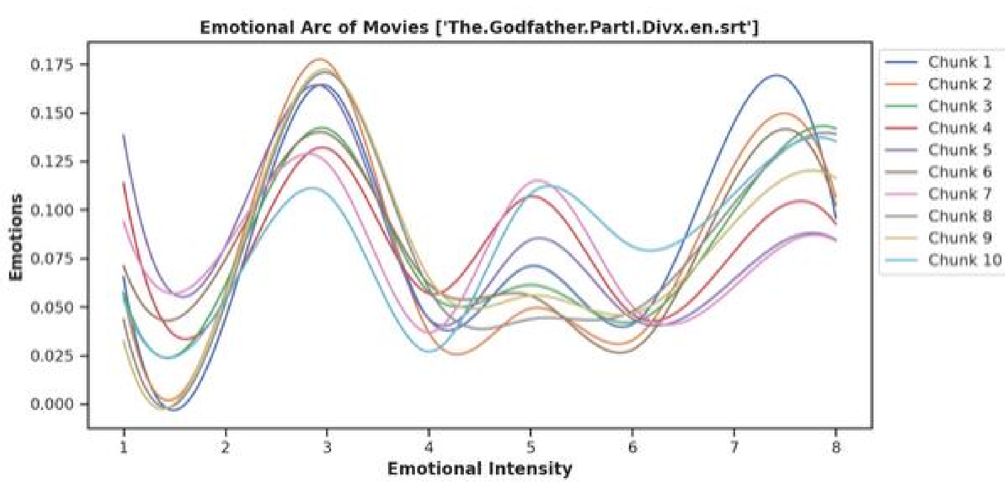


c

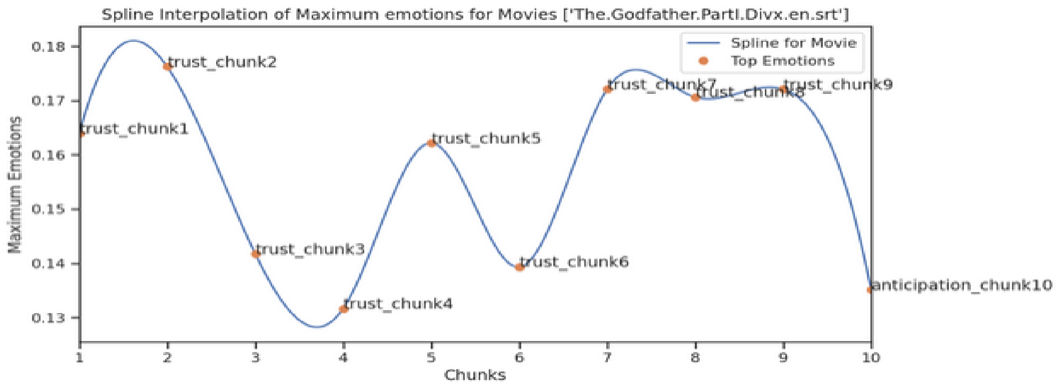
Figure 10 Emotional Arc of Man in Hole - Fall-Rise -Lords of Rings

- **Movie - God Father- Part1:**

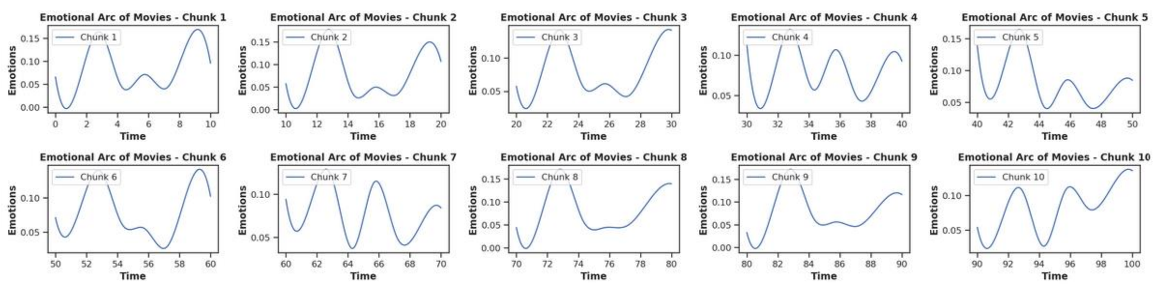
It's interesting to note that there is a statistically significant negative correlation between the Icarus cluster. The impact is noteworthy; according to Figure 11a and 11c, chunk 1 (the start chunk) and chunk 10 (the final chunk) indicate the emotional intensity Intial Fall and Raise moment, which denotes the Emotional arc of Man in a hole. The emotional flow of God Father Part1 is depicted in Figure 11b, where flow starts with positive emotion intensity begins at Trust (0.15 (15%)) & raised in initial chunk with high positive Trust (positive) (0.17(17%) and steep Fall towards emotion intensity of Low positive emotion of Trust (0.13(13%)) and end with Anticipation (positive emotion (0.14 (14%)). While Movie story line progress with high Positive emotions and Unexpected Fall in between and ends story line with positive emotion. Looks like People are crazier about stories where character or lead of story happy instance suddenly take unexpected twist to negative emotion and how that story ends in a happy note.



a



b



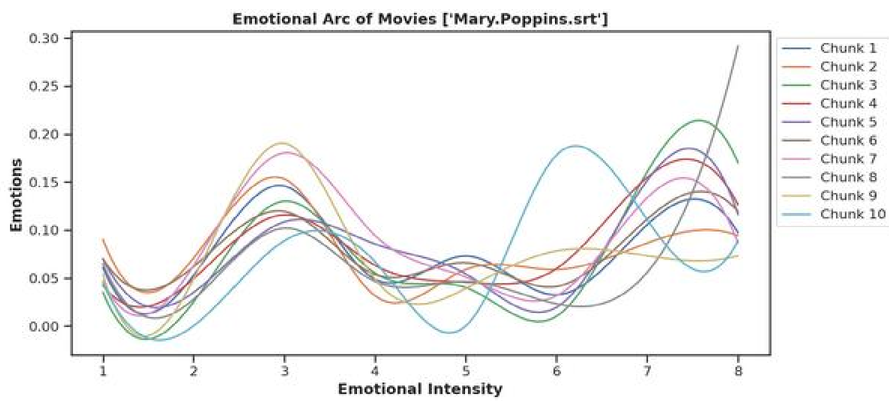
c

Figure 11 Emotional Arc of Man in Hole - Fall-Rise God father part-1

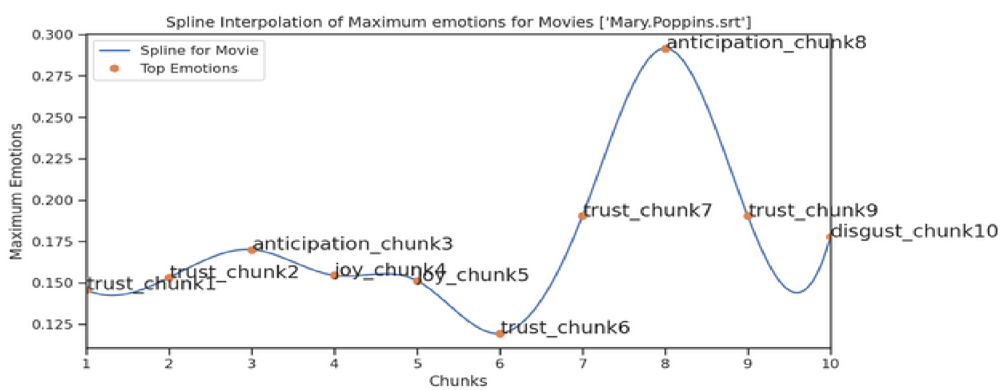
Emotional Arc of Icarus - Rise-Fall

- **Movie - Marry Poppins:**

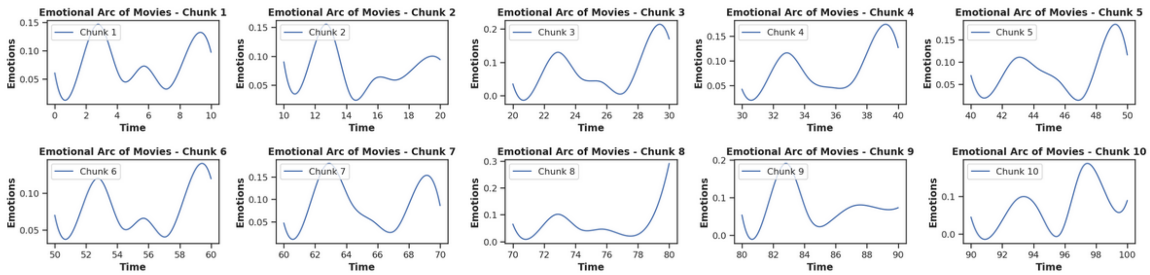
The emotional flow of Marry Poppins is depicted in Figure12b, where flow starts with positive emotion intensity begins at Trust (0.15 (15%)) & remaining low positive emotions stay in the same level for half of the story line and sudden spike in the mid raised in with high positive anticipation (positive) (0.20 -(20%) and steep Fall towards emotion intensity of Low negative emotion of disgust (0.17(17%)) at the tail end. This shows Rise and Fall in the emotions. To Infer, a book requires more time to consume than a movie does. Consequently, people may not want to experience an emotional fall that is not followed by an equivalent or nearly equivalent emotional rise in a time-limited environment, which could be one reason why the Icarus movies do not perform as well as the Icarus Rise fall Marry Poppins.



a



b

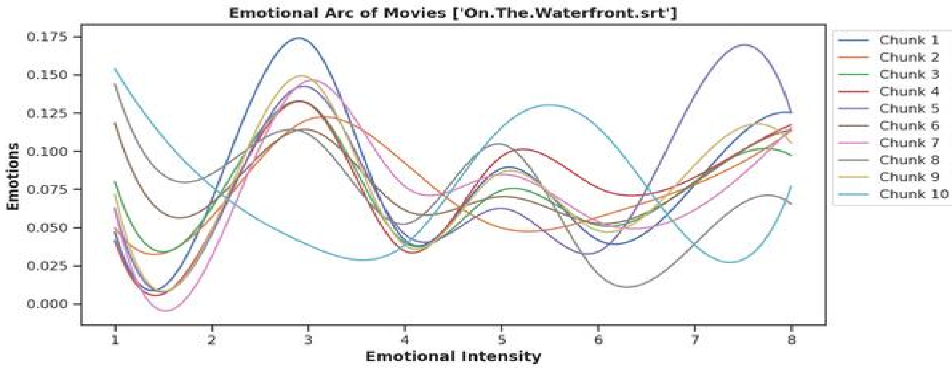


c

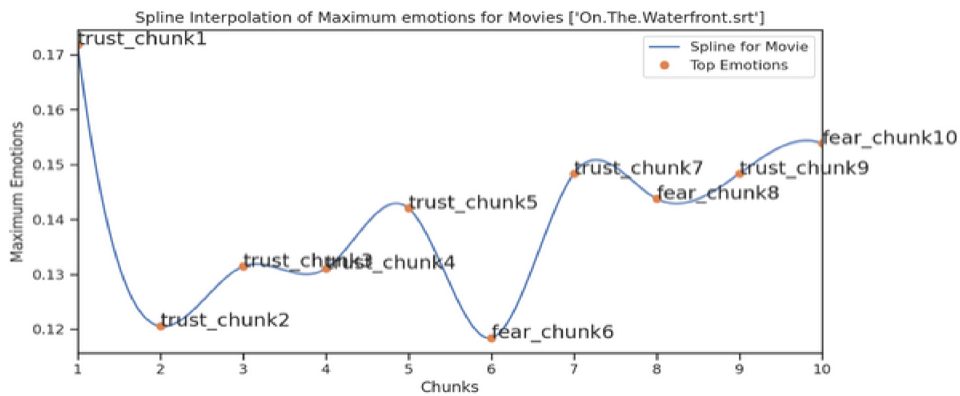
Figure 12 Emotional Arc of Icarus - Rise-Fall Marry Poppins

- **Movie - On the waterfront:**

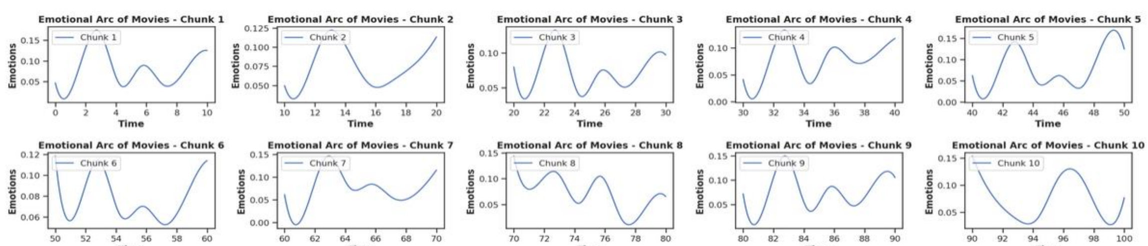
The emotional flow of movie on the waterfront is depicted in Figure 13b, where flow starts with positive emotion intensity begins at Trust (0.17 (17%)) & dropped low positive emotions stay in the same level for half of the story line and sudden drop in the mid raised in with high negative fear(negative) (0.12 -(12%) and small raise towards emotion intensity of Low negative emotion of fear (0.17(17%)) at the tail end. This shows Rise and Fall in the emotions. To infer, watching a movie takes less time than reading a book. Among the factors influencing the Icarus movies' inferior performance is People may not want to go through an emotional downturn in a time-limited setting on the waterfront if there isn't a corresponding or almost corresponding emotional upturn.



a



b



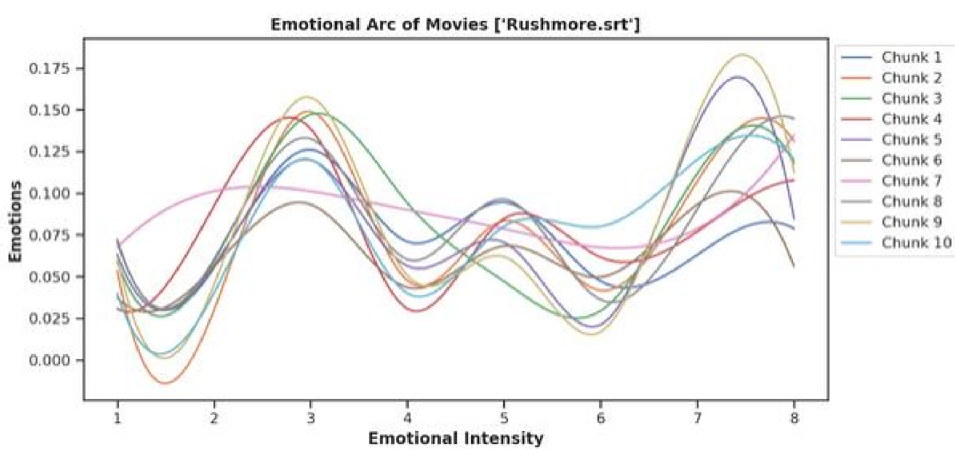
c

Figure 13 Emotional Arc of Icarus - Rise-Fall On the waterfront

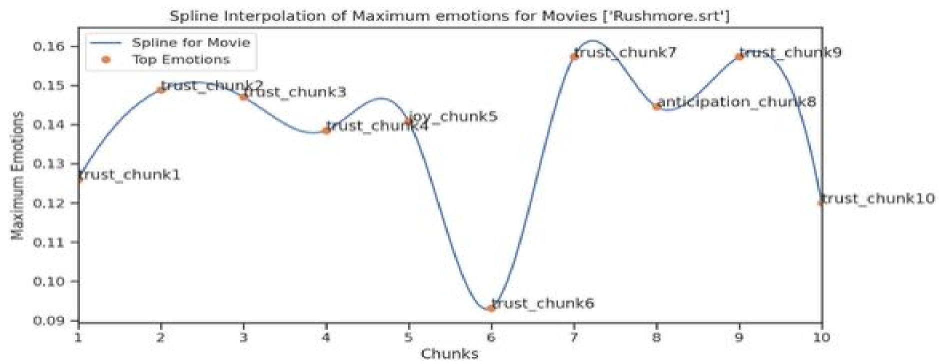
Emotional Arc of Cinderella - Rise-Fall-Rise

- **Movie - Rushmore:**

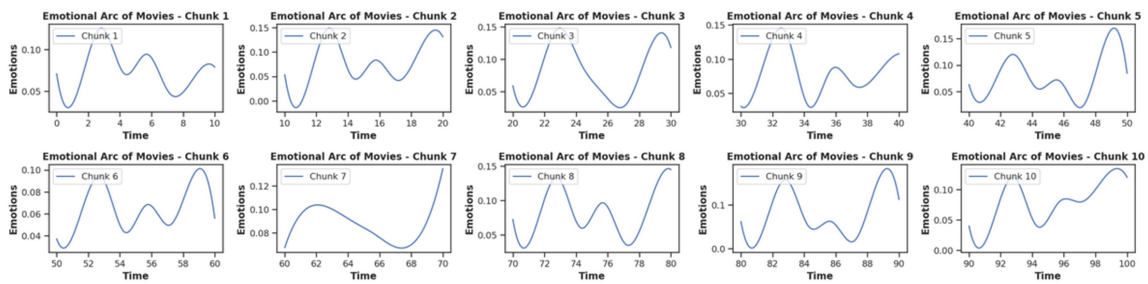
The emotional flow of movie on the Rushmore is depicted in Figure 14b, where flow starts with positive emotion intensity begins at Trust (0.13 (13%)) & will rise in emotions positive emotion trust (0.15 -(15%) and Fall towards emotion intensity of Low positive emotion of trust (0.05(5%)) and then Rise towards emotional intensity of Trust (0.15 (15%) and settles are positive emotion Trust at the tail end. Despite an emotional dip in the middle of the movie, the Cinderella Rise-Fall-Rise Rushmore emotional trajectory, on the other hand, shows a noticeable emotional rise towards the story's conclusion. Moviegoers may be more drawn to this emotional high than make-a-reservation viewers.



a



b

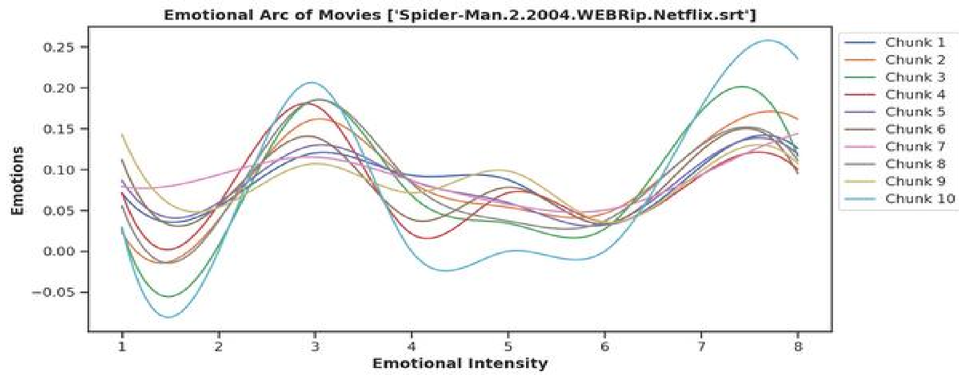


c

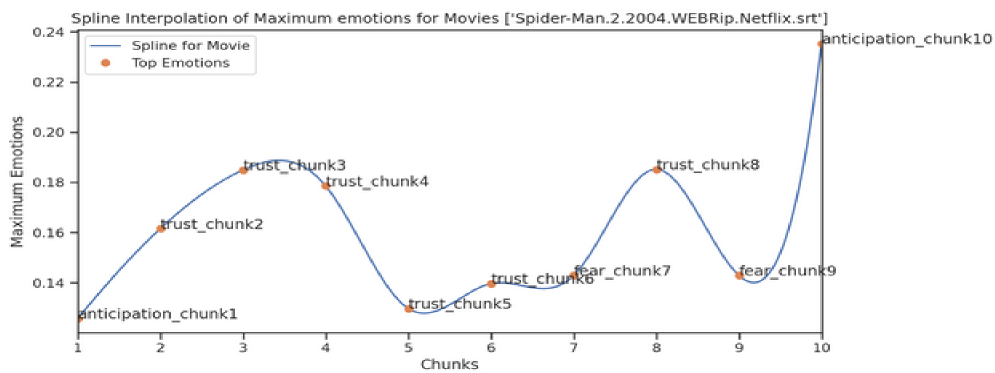
Figure 14 Emotional Arc of Cinderella - Rise-Fall-Rise- Rushmore

- **Movie - SpiderMan2:**

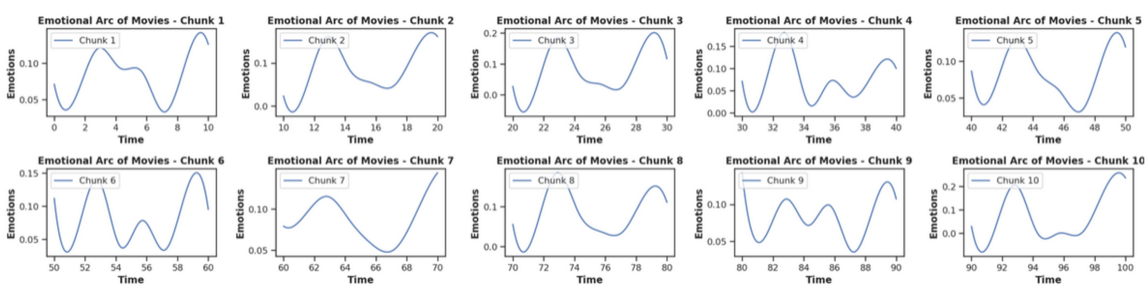
The emotional flow of movie on the Spiderman2 is depicted in Figure 15b, where flow starts with positive emotion intensity begins at Anticipation (0.03 (3%)) & will rise in emotions positive emotion trust (0.19 -(19%) and fall towards emotion intensity of Low positive emotion of trust (0.03(3%)) and then Rise towards positive emotional intensity of anticipation (0.15 (15%) at the tail end. Spiderman2 exhibits a noticeable emotional rise toward the story's conclusion, despite an emotional dip in the middle of the film. This emotional high might be more alluring to moviegoers than limitations.



a



b



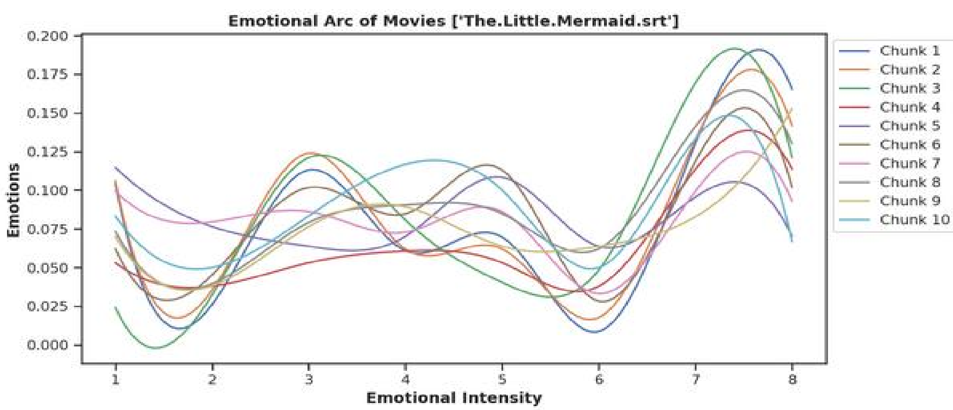
c

Figure 15 Emotional Arc of Cinderella - Rise-Fall-Rise -spider Man2

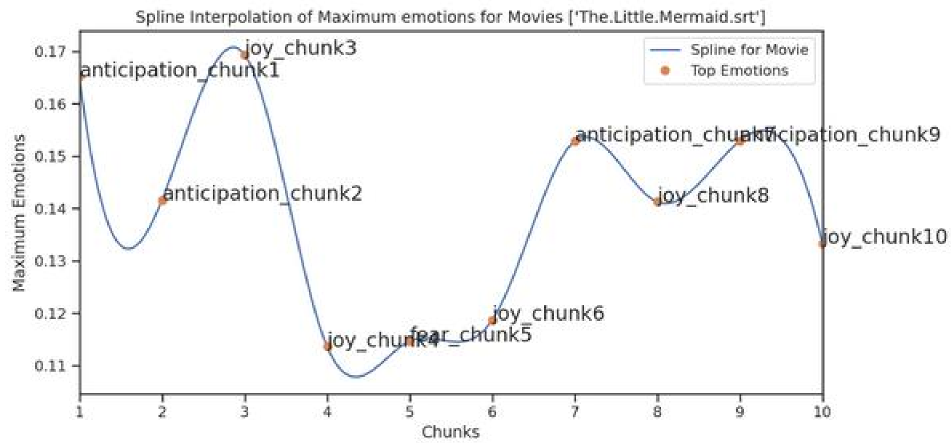
Emotional Arc of Oedipus - Fall-Rise-Fall

- **Movie - Little Mermaid:**

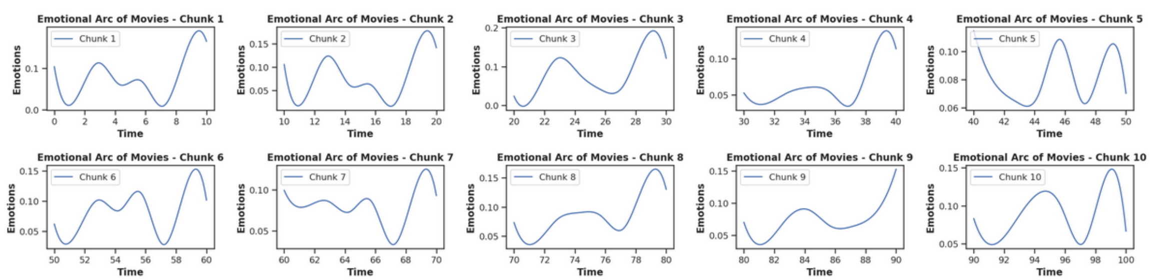
It's interesting to note that there is a statistically significant negative correlation between the Cinderella cluster. The emotional flow of movie on the Little Mermaid is depicted in Figure 16b, where flow starts with positive emotion intensity begins at anticipation (0.15 (15%)) & will rise in emotions positive emotion joy (0.17 -(17%) and fall towards emotion intensity of Low negative emotion of feat (0.12(12%)) and then Rise towards positive emotional intensity of anticipation (0.15 (15%) and settle at joy (0.12(12%)) at the tail end. A lower number of ratings and evaluations are obtained for the Oedipus Fall-Rise-Fall Little Mermaid cluster than for the other clusters.



a



b

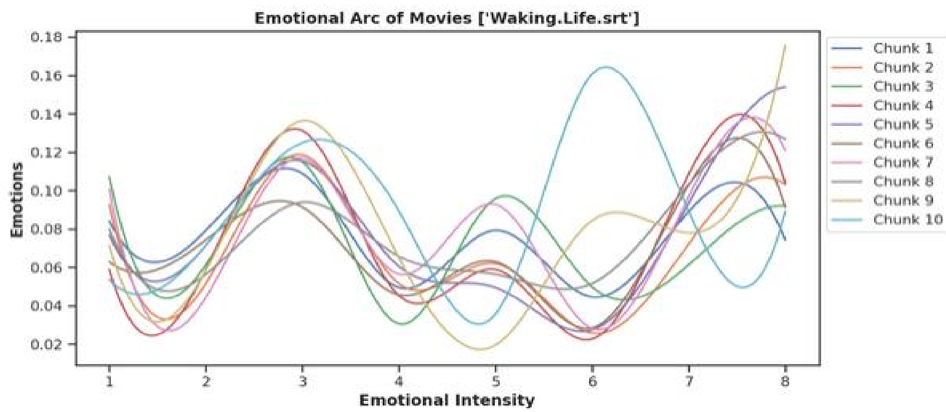


c

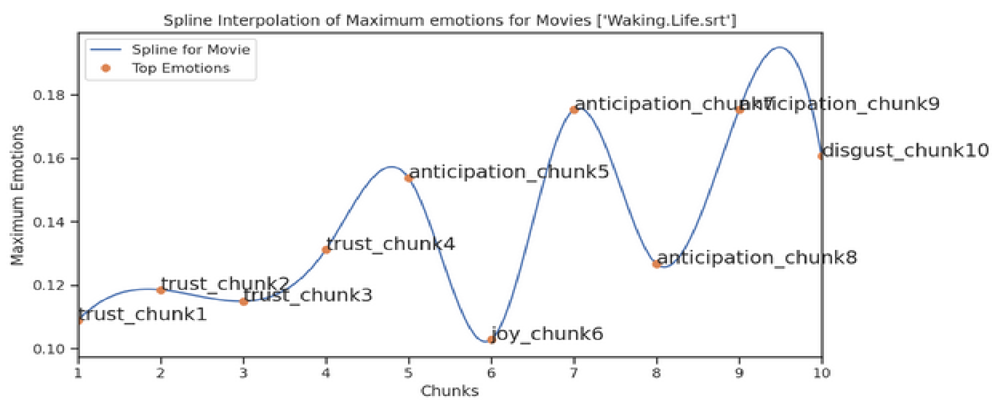
Figure 16 Emotional Arc of Oedipus- Fall-Rise-Fall Little Mermaid

- **Movie - Walking Life:**

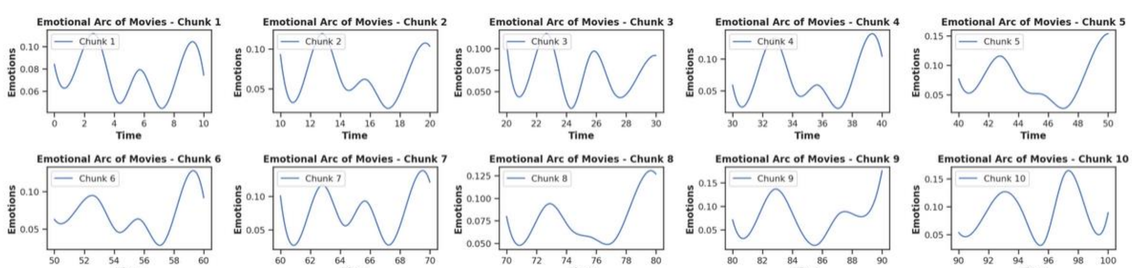
The emotional flow of movie on the Walking Life is depicted in Figure 17b, where flow starts with positive emotion intensity begins at Trust and reaches to Anticipation (0.15 (15%)) & then Fall positive emotion trust (0.10 -(10%) and rise towards emotion intensity of high positive emotion of anticipation (0.18(18%)) and then settles towards high negative emotional intensity of disgust (0.16 (16%) at the tail end. The Oedipus Fall-Rise-Fall Walking Life cluster yields fewer evaluations and ratings in contrast to other clusters.



a



b



c

Figure 17 Emotional Arc of Oedipus- Fall-Rise-Fall Walking Life

Rags to Riches Movies output:

While Movie story line progress with Positive emotions and ends with high positive emotion. The Riches to Rags cluster, interestingly, has a statistically significant negative correlation with domestic gross revenue or profit. According to critics typically favor serious films (perhaps with a tragic conclusion), and these films also typically do poorly financially.

Riches to Rags Emotional Arc output:

While Movie story line progress with low Positive emotions and ends with high negative emotion. Riches to Rags movies do better than rags to riches well financially. As per my inference, People who comes to watch movies would like to spend some quality time, then feeling sad which results in low turnout and movie doesn't do good.

Man in a Hole Output:

In contrast with other emotional arc, Man in Hole Movie story line progress with Unexpected Fall and ends story line with positive emotion. In contrast, Man in Hole films typically bring in a lot of money in most genres. Emotional arcs vary considerably, as evidenced by the genre combinations that show that, aside from Icarus, many emotional arcs could theoretically be connected to commercially successful films.

Icarus Emotional Arc of Movies:

Movies of the Icarus genre typically do well when they are low to medium-expenditure productions, and they do poorly when they demand a significant financial investment. Films featuring Icarus, regardless of genre, typically have poor box office performance; in contrast, Man in Hole films typically have strong sales in most genres. There is some diversity in the emotional arcs; the combinations of genres show that, aside from Icarus, many emotional arcs could theoretically be connected to commercially successful films. However, it is also evident that in most genre variations, the Man in a Hole emotional arc performs better financially than other arcs.

Cinderella Emotional Arc of Movies:

In theaters, Cinderella's trajectory performs better than Icarus'. This could suggest that people's ideal feelings are contingent upon how long their experiences last. it is reasonable to suppose that watching a movie will allow one to experience the same story faster than reading a book. On the other hand, during a longer period when the intensity of emotional fall is diffused, such as when reading a book, people are quite content to experience such a dramatic fall. On the other hand, despite the emotional dip in the middle of the film, Cinderella's emotional trajectory shows a discernible emotional rise towards the conclusion of the tale. Those who watch the movies might be more interested in this emotional rise than those who read the books.

Oedipus Emotional Arc of Movies

In comparison to other clusters, the Oedipus cluster produces comparatively few ratings and reviews. The average indicators rank the Oedipus cluster among the top 3 earning arcs. However, the cluster has a negative correlation with gross domestic revenue; however, this correlation is not statistically significant. A negative correlation is also produced by this cluster with non-Oscar nominations and awards. More specifically, compared to all other clusters, Oedipus films have the lowest chance of being nominated for and winning non-Oscar awards. Fascinatingly, Oscars are typically linked to increased domestic and international revenue. But this might also be a result of the fact that films that are nominated for an Oscar tend to gain more attention after winning one, as well as the fact that production companies usually choose their release dates carefully.

Final Output of Emotional Arc of Movies:

This section investigates the validity of our findings and tests our hypotheses. We discover that all the examined movie scripts can be divided into six main emotional trajectories (clusters), much like novels. Each trajectory is obtained by applying the clustering method outlined in Section. This supports the first hypothesis we put forth. All six clusters of emotional trajectories are depicted in Figure 18, along with movie samples that fit into each cluster. It shows that Emotional Arc "Man in a hole" has a greater number of movies in our sample. In Figure 19 where we plotted for Top10 most profitable movie by emotional arc it depicts most profitable movies are "Man in a hole" emotional arc.

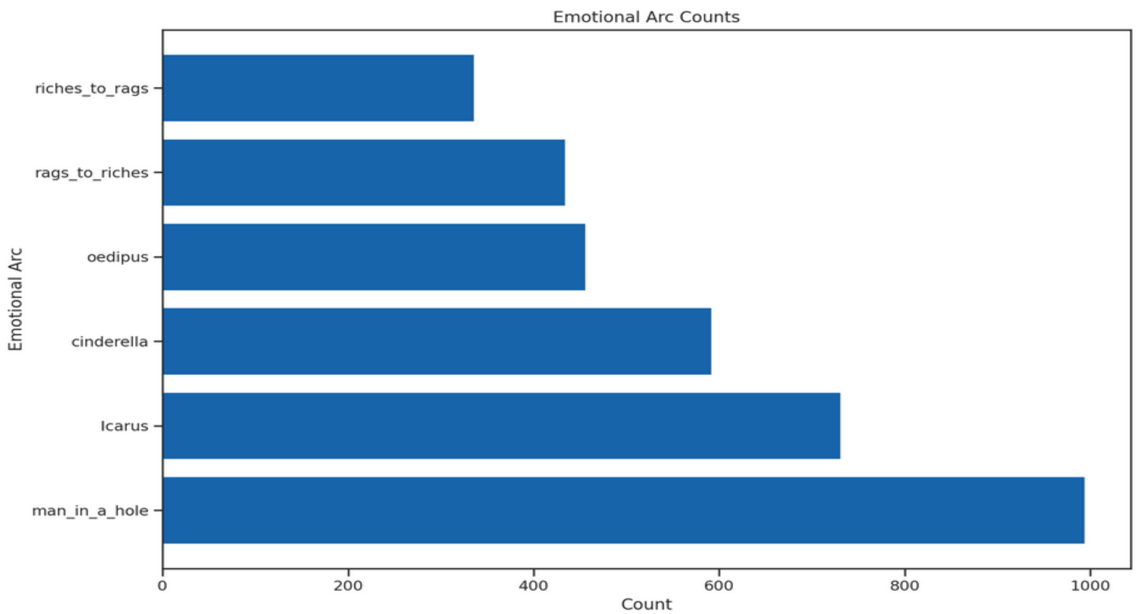


Figure 18 Final Output of Emotional Arc of Movies

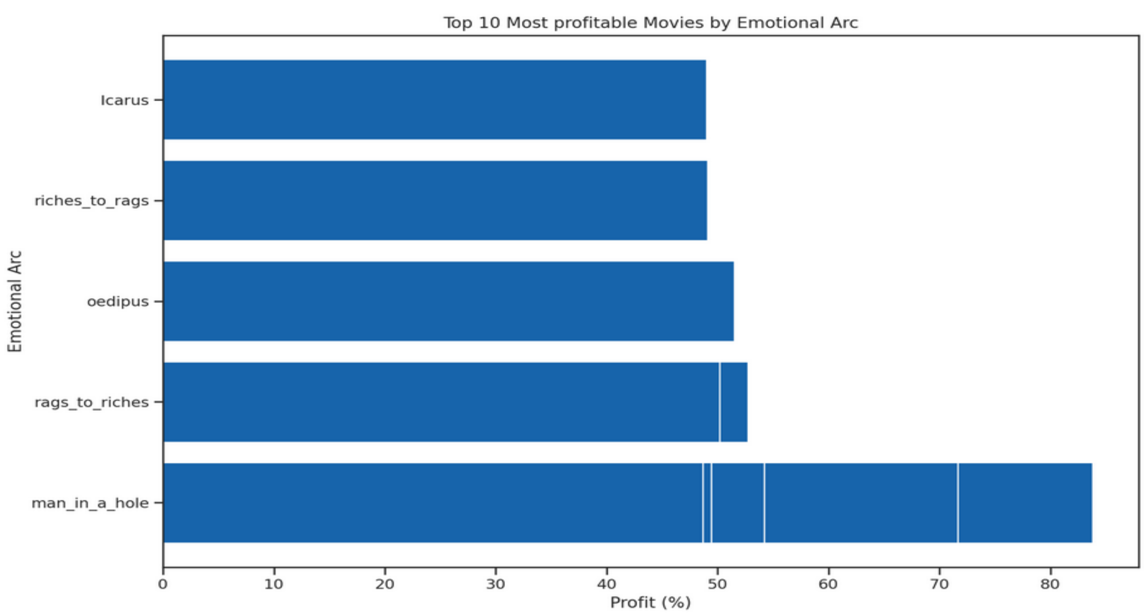


Figure 19 Top 10 Output of Emotional Arc of Movies

4.4 Conclusion

In a real interactive digital storytelling system, humans are an integral part of the system, and their primary objectives in this system are knowledge creation and meaningful interaction. More precise predictions of viewer preferences can be made thanks to recent developments in data science, which have improved our understanding of emotions. We investigated whether and to what degree emotions influence consumers' preferences and Emotional journey of stories for media and entertainment content in our most recent study using data science NLP methodology. After analyzing thousands of screenplays, we have determined that six main emotional trajectories can be distinguished from one another: Rags to Riches, Riches to Rags, Man in a Hole, Icarus, Cinderella, and Oedipus. We also discover that Man in a Hole, one of these trajectories, is typically more financially successful than other emotional arcs. Additionally, this relative success without regard to the genre of the film and regard to the budget allocated for its production.

CHAPTER V:

DISCUSSION

5.1 Discussion of Results

It is very difficult to increase productivity in the entertainment industry because film production teams frequently make less-than-ideal decisions to reduce production costs rather than increase revenue through better content creation, due to the complexity of the creative domain (Del Vecchio, et al., 2021). Numerous theoretical, methodological, empirical, and practical contributions are made by this paper.

Our primary theoretical contribution is to show how recent developments in data science enable us to gain a deeper understanding of human emotions and apply this understanding to predict viewer preferences more precisely. This kind of analytics makes it possible to better tailor created content to consumer preferences, which boosts movie production revenue. We present a novel conceptual framework that explores how data science can enhance the movie creation value chain. We validate this framework using publicly accessible data.

In terms of methodology, we investigate whether and to what extent emotions influence consumer preferences for media and entertainment content using econometric analysis and data science natural language processing tools. We discover that six main emotional trajectories can be distinguished from each other among the analyzed emotional arcs of thousands of motion picture scripts: Rags to Riches, Riches to Rags, Man in a Hole, Icarus, Cinderella, and Oedipus. Similar findings from earlier studies on emotional shapes in books (Reagan et al., 2016) assisted us in developing our theoretical hypotheses since popular films are usually based on best-selling books (Del Vecchio, et al., 2018; Chu & Roy, 2017).

Empirically, we discover that Man in a Hole, one of the six trajectories, is typically more financially successful than the other emotional arcs. Moreover, this relative success is evident regardless of the genre of the film and is independent of the production budget. If the rating on IMDb serves as a surrogate for viewer satisfaction, we can deduce that the reason why films with the Man in the Hole emotional arc are so successful is not because they produce the most popular films (i.e., the ones with the highest ratings on IMDb), but rather because they are the most unique and provocative.

It is important to note that we wouldn't recommend employing this method in place of hiring professional producers or scriptwriters. Instead, our method serves as a solid illustration of a possible decision support system. Our method gives screenwriters the chance to test their scripts for emotional arcs, giving them a point of reference while they write. Our method provides a way out of the increasing problem for producers of having to deal with the large number of incoming screenplays and the ensuing human error (Kasunic & Kaufman, 2018). By using data science to inform the script selection process, it is possible to make unconventional decisions that have unanticipated benefits and to further diversify the film offerings. Furthermore, our method adds quantifiable metrics and tangible numbers to a situation that has hitherto mostly relied on expert intuition and subjective analysis.

Our research indicates that companies should diversify their approach by allocating a portion of their budgets to content that is expected to perform well, such as Man in Hole movies, given the high cost of motion pictures and creative content production.

There are several restrictions on this study. To begin with, all the data used in this paper came from sources that were open to the public. Second, our clustering analysis makes use of subtitles rather than full scripts. Third, our dataset did not contain all the movies for which we were unable to locate subtitles. A more pristine method of testing our econometric model would be to utilize past script data from a film studio (Hwangbo & Kim, 2019). The studio is currently considering new scripts, which we would use to generate clustering from that historical data to forecast revenue. After the film's release, the revenue could be evaluated in comparison to our projection.

5.2 Discussion of Research Question One

Our research to date indicates that the Man in a Hole emotional trajectory generates the highest overweight local revenue, which partially validates our second prediction. Furthermore, we found that this emotional trajectory earns the most money not because it produces the most "liked" content but rather because if IMDb ratings accurately reflect viewer satisfaction rates. Rather, viewers pay the greatest attention to the movies in this cluster. Next, we will check the robustness of our findings by looking at whether and how production budgets affect revenues. Films are expensive to produce, so it's important to understand whether and to what extent high profits are associated with the initial investment in the film's production. To investigate this issue, we look at the estimated production budgets for a subsample of our dataset that we got from the com repository.

Once the dataset has been extracted, redundant and unwanted features must be eliminated. Following that, we used text preprocessing to clean the subtitles for every movie. For each text chunk, an NRCLex object is created using the ***NRCLex(segment)*** instantiation. NRCLex then processes the text chunk and uses the NRC Emotion Lexicon to identify and count the occurrences of words associated with each emotion category (anger, fear, anticipation, trust, surprise, sadness, joy, disgust, negative, and positive). The affect_frequencies attribute of the NRCLex object is then used to retrieve a dictionary of emotion counts for the given text chunk.

The dictionary includes the frequencies of words associated with each emotion category. The emotion counts for each chunk are collected and stored in the emotion_counts_all lists. This list will contain dictionaries where keys are emotion categories, and values are the corresponding frequencies in each chunk. The code defines a function `exclude_keys(emotion_count) ` to exclude the 'positive' and 'negative' keys from the emotion count dictionary. This step is performed to focus on the eight basic emotions rather than sentiments.

The code defines a function `exclude_keys` to exclude the 'positive' and 'negative' keys from the emotion count dictionary. All the DataFrames created in the previous step are concatenated along the columns to form a single DataFrame (`final_df`) for a set of chunks. This process is repeated for all sets of chunks, and the resulting Data Frames are stored in the `final_df1` list.

5.3 Discussion of Research Question Two

The NRC (National Research Council) Emotion Lexicon is a widely used lexicon that associates words with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). NRCLex, a Python library, is built upon this lexicon and provides a way to analyze the emotion content of a given text. The NRC Emotion Lexicon contains a list of words along with their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). Each word is labeled with binary values indicating the presence or absence of these emotions or sentiments.

NRCLex is known for providing fine-grained emotion analysis by categorizing text into eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, disgust) and two sentiments (positive and negative). It uses a lexicon-based approach, leveraging a manually curated lexicon that associates words with emotions. This approach can be beneficial for capturing nuanced emotional content.

AFINN is a simple and fast method for sentiment analysis. It assigns a pre-computed sentiment score to each word and calculates the overall sentiment score for a text based on these scores.

AFINN primarily focuses on sentiment analysis and provides a single positive/negative score for a given text. It lacks the granularity of NRCLex in terms of distinguishing between different emotions. The model may struggle with capturing nuances in emotional content beyond a binary positive/negative sentiment.

EMoBERTa is based on BERT (Bidirectional Encoder Representations from Transformers), a powerful pre-trained language model. It can capture complex contextual information and understand the relationships between words in a sentence. BERT-based models, including EMoBERTa, can be computationally intensive, requiring substantial resources for training and inference.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

Humans are an essential component of a real interactive digital storytelling system, and their main goals are meaningful interaction and knowledge creation. Our understanding of emotions has improved due to recent AI and ML developments, which allow for more accurate predictions of viewer preferences. In our most recent study, we used Natural language processing (NLP) methodology to examine whether and to what extent consumers' preferences for media and entertainment content are influenced by emotions. Six primary emotional trajectories Rages to Riches, Riches to Rags, Man in a Hole, Icarus, Cinderella, and Oedipus can be distinguished from one another, according to our analysis of thousands of screenplays. We also learn that, compared to other emotional arcs, Man in a Hole, one of these trajectories, is usually more financially successful. Furthermore, it is evident that this relative success occurs regardless of the film's genre, or the production budget allotted for it.

6.2 Implications

On the one hand, film production companies should prioritize screenplays that offer emotional journeys for the Man in the Hole when assessing movie scripts. Conversely, though, this would oversimplify our findings. We demonstrate that any of the six emotional arcs can result in commercially successful movies when they are blended with other genres and made in various budget ranges. As a result, choosing the right script, budget, and genre combination carefully will increase revenue, decrease the number of failures, and boost output. But data science can greatly improve the communication between film studios and audiences as well as help create "on demand," "customer-centric," and even personalized content that moviegoers would be interested in buying. The decision-making process regarding desirable content may be shifted from producers to consumers if sentiment analysis of movies is a crucial component of the business model selection process. This would give viewers a powerful voice in shaping or even influencing the creation of motion images.

6.3 Recommendations for Future Research

Through future preference mapping, our results show that data science, AI and ML can improve revenue streams and, consequently, productivity. Practice is beginning to validate this approach already. Data-driven content creation has clear advantages when compared to traditional motion picture studios like Disney, 21st Century Fox (Disney-Fox studios merged into one company in March 2019), Warner Brothers, Universal, Sony/Columbia, Paramount, and Lionsgate. This is especially evident when comparing the financial performance of companies that actively use AI and ML for content creation, like Netflix. See https://cloud.google.com/blog/products/ai machine-learning/how-21st-century-fox-uses-ml-to JOURNAL OF THE OPERATIONAL RESEARCH for a thorough example of how AI and ML is used in motion picture production at 21st Century Fox. It is evident that Netflix has chosen a more successful course of action than the traditional companies by implementing data-driven content creation (Kim, Kang and Jeong, 2018b; Zhou, Zhang and Yi, 2019c)

According to our research, companies should diversify their strategy by allocating a portion of their budgets to content that is expected to perform well, such as Man in Hole movies, given the high cost of motion pictures and creative content production. These "low risk" investments would enable these businesses to allocate a portion of their funds for high-risk endeavors (like art-house films). A prime example of a company using data science, AI and ML strategically and creatively for content creation is Netflix. 2018 saw the widespread acclaim of Alfonso Cuaron's Netflix film "Roma," which won three Academy Awards, including Best Foreign Language Film, Best Director, and Best Cinematography. It is up to future research to test our method in a more hygienic setting (Kasunic and Kaufman, 2018c). Further investigation into the robustness of our clusters using various clustering techniques would be an intriguing project. We believe that more accurate methods of measuring productivity in the creative industries will be developed and put to the test empirically in the coming years.

6.4 Conclusion

Recent developments in data science, AI and ML enable us to anticipate viewer preferences more precisely by providing a deeper understanding of emotions. In a recent study, we investigated whether and to what degree consumer preferences for media and entertainment content are influenced by emotions using data science, Machine Learning(ML) and

Artificial Intelligence (AI) methodology. These findings enable us to investigate a further aspect of the movie's success. Our research reveals that, although the revenue from films based on different genres Rages to Riches, Riches to Rags, Cinderella, and Oedipus, for example, Icarus films are typically financially unsuccessful regardless of the genre, while Man in Hole films tend to do well financially across most genres (Zhou, Zhang and Yi, 2019c; Del Vecchio *et al.*, 2021b) and showed in Figure 18. There is some diversity in the emotional arcs; the combinations of genres show that, aside from Icarus, many emotional arcs could theoretically be connected to commercially successful films. However, it is also evident that in most genre variations, the Man in a Hole emotional arc performs better financially than other arcs. Moreover, this relative success is evident regardless of the genre of the film and is independent of the production budget. If the rating on IMDb serves as a surrogate for viewer satisfaction, we can also deduce that the success of the Man in a Hole emotional arc is attributed to the fact that these films tend to be the most unique and provocative, rather than because the public seeks out these films (i.e., they receive the highest ratings on IMDb). Put another way, films with the Man in a Hole emotional arc tend to be the most "talked about" rather than the "most liked," and as a result, they earn more money than films in other genres.

REFERENCES

Aarseth, E. (2003). Playing Research: Methodological approaches to game analysis. Game Studies, 3(1).

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6), 734–749.

Ahmed, U., Waqas, H. and Afzal, M.T., 2020. Pre-production box-office success quotient forecasting. Soft Computing, 24(9), pp.6635-6653.

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In J. Kuhl & J. Beckmann (Eds.), Action Control: From Cognition to Behavior (pp. 11–39). Springer.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.

Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Prentice-Hall.

Appadurai, A. (1996). Modernity at Large: Cultural Dimensions of Globalization. University of Minnesota Press.

Aristotle. (350 BCE). Poetics.

Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. British Journal of Social Psychology, 40(4), 471-499.

Asur, S., & Huberman, B. A. (2010). Predicting the future with social media. In Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (Vol. 1, pp. 492–499).

Bakhshi, S., Shamma, D. A., & Gilbert, E. (2016). Faces engage us: Photos with faces attract more likes and comments on Instagram. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 965-974.

Barsade, S. G., & Gibson, D. E. (2007). Why does affect matter in organizations? Academy of Management Perspectives, 21(1), 36-59.

Benjamin, R. (2019). Art after spectacle: Ethical capacity and the resuscitation of art. Journal of the British Society for Phenomenology, 50(3), 249-259.

Bertsimas, D., Gupta, V., & Wang, Y. (2018). The impact of data on analytics and optimization. INFORMS Journal on Optimization, 1(2), 71-91.

Bordwell, D., & Thompson, K. (2013). Film Art: An Introduction. McGraw-Hill Education.

Brabham, D. C. (2008). Crowdsourcing as a model for problem-solving an introduction and cases. Convergence: The International Journal of Research into New Media Technologies, 14(1), 75-90.

Branigan, E. (1992). Narrative Comprehension and Film. Routledge.

Brewer, W. F., & Lichtenstein, E. H. (1982). Stories Are to Entertain: A Structural-Affect Theory of Stories. Journal of Pragmatics, 6(5–6), 473–486.

Brose, A., Scheibe, S., Schmiedek, F., Lovden, M., & Lindenberger, U. (2013). Normal aging dampens the link between intrusive thoughts and negative affect in reaction to daily stressors. Psychology and Aging, 28(2), 530-541.

Bruner, J. (1991). The narrative construction of reality. Critical Inquiry, 18(1), 1-21.

Brynjolfsson, E., Hu, Y. J., & Smith, M. D. (2003). Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. Management Science, 49(11), 1580-1596.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., & Allas, T. (2018). Artificial Intelligence: The Next Digital Frontier? McKinsey Global Institute.

Cambria, E., & White, B. (2014). Jumping NLP curves: A review of natural language processing research. IEEE Computational Intelligence Magazine, 9(2), 48–57.

Cambria, E., Livingstone, A., & Hussain, A. (2013). The Hourglass of Emotions. In A. Esposito, A. Vinciarelli, R. Hoffmann, V. Müller, & M. Marinaro (Eds.), Cognitive Behavioral Systems (pp. 144–157). Springer.

Campbell, J. (1949). The Hero with a Thousand Faces. Princeton University Press.

Carrillat, F.A., Legoux, R. and Hadida, A.L., 2018. Debates and assumptions about motion picture performance: A meta-analysis. Journal of the Academy of Marketing Science, 46(2), pp.273-299.

Chen, M., Chiang, M., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. MIS Quarterly, 36(4), 1165–1188.

Cheng, L., Li, S., Wang, F., Zhang, L., Li, S., & Han, X. (2020). A review of generative design in product design. Virtual and Physical Prototyping, 15(2), 141-156.

Chew, W.B., 1988. No-nonsense guide to measuring productivity. Harvard Business Review, 66(1), pp.110-118.

Chu, E., & Roy, D. (2017, November). Audio-visual sentiment analysis for learning emotional arcs in movies. In 2017 IEEE International Conference on Data Mining (ICDM) (pp. 829-834). IEEE.

Chui, M., Manyika, J., & Mehra, S. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey Global Institute.

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. Journal of Personality and Social Psychology, 58(6), 1015-1026.

Conner, M., & Norman, P. (2005). Predicting health behaviour: Research and practice with social cognition models. McGraw-Hill Education.

Covington, P., Adams, J., & Sargin, E. (2016). Deep Neural Networks for YouTube Recommendations. Proceedings of the 10th ACM Conference on Recommender Systems.

Culkin, N., Morawetz, N. and Randle, K., 2008. Digital cinema as disruptive technology: exploring new business models in the age of digital distribution. In Information Communication Technologies: Concepts, Methodologies, Tools, and Applications (pp. 1832-1845). IGI Global.

D. A. Koene, S. J. Kim, M. Fisher, M. A. Nilsson, & T. R. Calvard (2019). Responsible AI in Hollywood: Creative Collaborations and Ethical Considerations. Convergence: The International Journal of Research into New Media Technologies, 26(2), 251-268.

Dashtipour, K., Gogate, M., Adeel, A., Larijani, H. and Hussain, A., 2021. Sentiment analysis of persian movie reviews using deep learning. Entropy, 23(5), p.596.

Davenport, T. H., & Harris, J. (2007). Competing on analytics: The new science of winning. Harvard Business Press.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

De Pater, I. E., Judge, T. A., & Scott, B. A. (2014). Age, gender, and compensation: A study of Hollywood movie stars. Journal of Management Inquiry, 23(4), 407-420.

Del Vecchio, M., Kharlamov, A., Parry, G. and Pogrebna, G., 2018. The Data science of Hollywood: Using emotional arcs of movies to drive business model innovation in entertainment industries. Available at SSRN 3198315.

Del Vecchio, M., Kharlamov, A., Parry, G. and Pogrebna, G., 2021. Improving productivity in Hollywood with data science: Using emotional arcs of movies to drive product and service innovation in entertainment industries. Journal of the Operational Research Society, 72(5), pp.1110-1137.

Derrida, J. (1967). Of Grammatology. Johns Hopkins University Press.

DeVito, M. A., & Birnholtz, J. P. (2016). Personalization in the Coming Age of Augmented Reality. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, 1265-1276.

Dholpuria, T., Rana, Y.K. and Agrawal, C., 2018, November. A Sentiment analysis approach through deep learning for a movie review. In 2018 8th International Conference on Communication Systems and Network Technologies (CSNT) (pp. 173-181). IEEE.

Duan, J., Ding, X. and Liu, T., 2017. A Gaussian copula regression model for movie box-office revenues prediction. Science China Information Sciences, 60(9), p.092103.

Dudoit, S., & Fridlyand, J. (2002). A prediction-based resampling method for estimating the number of clusters in a dataset. Genome Biology, 3(7), 0036.1–0036.21.

Duhigg, C. (2012). How companies learn your secrets. The New York Times Magazine.

Durkheim, E. (1893). The Division of Labor in Society. Free Press.

Durkheim, E. (1912). The Elementary Forms of the Religious Life. Free Press.

Ekman, P. (1992). An argument for basic emotions. Cognition & Emotion, 6(3-4), 169-200.

Ekstrand, M. D., Riedl, J. T., & Konstan, J. A. (2018). Collaborative Filtering Recommender Systems. Foundations and Trends® in Human–Computer Interaction, 12(2), 69–148.

Elberse, A., & Eliashberg, J. (2003). Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures. Marketing Science, 22(3), 329-354.

Elgammal, A., Liu, B., & Elhoseiny, M. (2017). CAN: Creative Adversarial Networks, Generating" Art" by Learning About Styles and Deviating from Style Norms. arXiv preprint arXiv:1706.07068.

Eliashberg, J., Elberse, A. and Leenders, M.A., 2006. The motion picture industry: Critical issues in practice, current research, and new research directions. Marketing science, 25(6), pp.638-661.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with

Field, S. (2005). Screenplay: The Foundations of Screenwriting. Bantam.

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Addison-Wesley.

Forster, E. M. (1927). Aspects of the Novel. Harvest Books.

Foucault, M. (1972). The Archaeology of Knowledge. Pantheon Books.

Fournier, S. (1998). Consumers and Their Brands: Developing Relationship Theory in Consumer Research. Journal of Consumer Research, 24(4), 343-353.

Fraser, M., Baele, S. J., & Morgan, M. (2003). Subjective norms and the intention–behavior relation: The role of norm salience. Basic and Applied Social Psychology, 25(3), 235-244.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), 137-144.

Geertz, C. (1973). The interpretation of cultures: Selected essays. Basic Books.

Ghiassi, M., Lio, D. and Moon, B., 2015. Pre-production forecasting of movie revenues with a dynamic artificial neural network. Expert Systems with Applications, 42(6), pp.3176-3193.

Ghiassi, M., Skinner, J., & Zimbra, D. (2013). Twitter brand sentiment analysis: A hybrid system using n-gram analysis and dynamic artificial neural network. Expert Systems with Applications, 40(16), 6266–6282.

Giddens, A. (1984). The constitution of society. University of California Press.

Giddens, A. (1986). The Constitution of Society. University of California Press.

Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). Deep Learning. MIT Press.

Gorbman, C. (1987). Unheard Melodies: Narrative Film Music. Indiana University Press.

Green, M. C., & Brock, T. C. (2000). The role of transportation in the persuasiveness of public narratives. Journal of Personality and Social Psychology, 79(5), 701–721.

Grigore, A. M., & Moisescu, M. A. (2019). Augmented reality in the entertainment industry: A literature review. Sustainability, 11(3), 762.

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. Review of General Psychology, 2(3), 271–299.

Hart, W., & Kupfer, T. R. (2015). An empirical test of the Aristotelian theory of tragedy in movie narratives. Journal of Personality and Social Psychology, 109(6), 956–977.

Hasselgren, B. (2018). Generative design: A design method for today's manufacturing industry. Computers in Industry, 95, 1-12.

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1994). Emotional contagion. Cambridge University Press.

Hochschild, A. R. (1979). Emotion work, feeling rules, and social structure. American Journal of Sociology, 85(3), 551-575.

Holstein, K., & Verhulst, S. G. (2019). Deep learning and the art of representation. AI & Society, 34(2), 219-235.

Holzinger, A., Langs, G., Denk, H., Zatloukal, K., & Müller, H. (2017). Causability and explainability of artificial intelligence in medicine. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 7(6), e1213.

Hsu, C. L. (2019). Influencer marketing: Exploring consumer's purchase intention. Journal of Marketing Communications, 25(6), 520-532.

Hu, R., Pu, P., Chen, L., & Liu, Q. (2008). A Balanced and Cooperative Framework for Service Recommendation. In Proceedings of the 2008 ACM Conference on Recommender Systems (pp. 49–56).

Hur, M., Kang, P. and Cho, S., 2016. Box-office forecasting based on sentiments of movie reviews and independent subspace method. Information Sciences, 372, pp.608-624.

Hwangbo, H., & Kim, J. (2019). A text mining approach for sustainable performance in the film industry. Sustainability, 11(11), 3207.

Jain, V. (2013). Prediction of movie success using sentiment analysis of tweets. The International Journal of Soft Computing and Software Engineering, 3(3), 308-313.

Jasper, J. M. (1998). The emotions of protest: Affective and reactive emotions in and around social movements. Sociological Forum, 13(3), 397-424.

Jing, Y., & Smola, A. (2017). Neural Collaborative Filtering. Proceedings of the 26th International Conference on World Wide Web.

Jockel, S. and Dobler, T., 2006. The event movie: Marketing filmed entertainment for transnational media corporations. The International Journal on Media Management, 8(2), pp.84-91.

Joshi, S., & Sharda, R. (2020). Sentiment Analysis in the Age of Artificial Intelligence: A Comprehensive Review. IEEE Transactions on Computational Social Systems.

Joulin, A., Grave, E., Bojanowski, P., Mikolov, T., Bagheri, M., Lample, G., ... & Auli, M. (2017). FastText.zip: Compressing text classification models. arXiv preprint arXiv:1612.03651.

Kasunic, A. and Kaufman, G., 2018, June. Learning to Listen: Critically Considering the Role of AI in Human Storytelling and Character Creation. In Proceedings of the First Workshop on Storytelling (pp. 1-13).

Keen, S. (2006). A Theory of Narrative Empathy. Narrative, 14(3), 207-236.

Kim, T., Hong, J. and Kang, P., 2015. Box office forecasting using machine learning algorithms based on SNS data. International Journal of Forecasting, 31(2), pp.364-390.

Kim, Y., Kang, M. and Jeong, S.R., 2018. Text mining and sentiment analysis for predicting box office success. KSII Transactions on Internet and Information Systems (TIIS), 12(8), pp.4090-4102.

Kiritchenko, S., Zhu, X., & Mohammad, S. M. (2014). Sentiment analysis of short informal texts. Journal of Artificial Intelligence Research, 50, 723–762.

Kreuter, M. W., Green, M. C., Cappella, J. N., Slater, M. D., Wise, M. E., Storey, D., Clark, E. M., & O'Keefe, D. J. (2007). Narrative communication in cancer prevention and control: A framework to guide research and application. Annals of Behavioral Medicine, 33(3), 221-235.

Kung, C., Song, Y., & Oh, J. S. (2017). Social media analytics: A survey of techniques, tools and platforms. Management Decision, 55(4), 701-722.

Lazarus, R. S. (1993). From psychological stress to the emotions: A history of changing outlooks. Annual Review of Psychology, 44, 1-21.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.

Litman, B. R. (2018). Digital copyright: The end of an era. Oxford University Press.

Liu, B. (2012). Sentiment Analysis and Opinion Mining. Morgan & Claypool Publishers.

Liu, B. (2015). Sentiment analysis: Mining opinions, sentiments, and emotions. Cambridge University Press.

Loewenstein, G., & Lerner, J. S. (2003). The role of affect in decision making. In Handbook of affective sciences (pp. 619-642). Oxford University Press.

Manstead, A. S. R., & Fischer, A. H. (2001). Social appraisal: The social world as object of and influence on appraisal processes. In Appraisal processes in emotion: Theory, methods, research (pp. 221–232). Oxford University Press.

Marco Del Vecchio, Alexander Kharlamov, Glenn Parry, & Ganna Pogrebna. (2020). Improving productivity in Hollywood with data science: Using emotional arcs of movies to drive product and service innovation in entertainment industries. Journal of the Operational Research Society, 72(5), 1110–1137. doi:10.1080/01605682.2019.1705194

Marco Del Vecchio, Alexander Kharlamov, Glenn Parry, & Ganna Pogrebna. (2018). The Data Science of Hollywood: Using Emotional Arcs of Movies to Drive Business Model Innovation in Entertainment Industries. Social Science Research Network. doi:10.2139/ssrn.3198315

Marx, K., & Engels, F. (1848). The Communist Manifesto. Trans. S. Moore.

McCarthy, M. (2011). Story: Style, Structure, Substance, and the Principles of Screenwriting. HarperCollins.

McCosker, A., Wilken, R., & Wilken, R. (2018). Rethinking 'Creative Cities' from the Margins: Artificial Intelligence (AI) and Cultural Work. Media International Australia, 168(1), 56-69.

McKee, R. (1997). Story: Substance, Structure, Style and the Principles of Screenwriting. HarperCollins.

McLuhan, M. (1964). Understanding media: The extensions of man. McGraw-Hill.

Mead, G. H. (1934). Mind, Self, and Society. University of Chicago Press.

Merton, R. K. (1957). Social theory and social structure. Free Press.

Mitchell, T. M. (1997). Machine Learning. McGraw-Hill.

Mollahosseini, A., Chan, D., & Mahoor, M. H. (2017). Going deeper in facial expression recognition using deep neural networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 1892-1901.

Murray, J. H. (1997). Hamlet on the Holodeck: The Future of Narrative in Cyberspace. Free Press.

Mykhailychenko, R., 2019. The 4th industrial revolution: responding to the impact of artificial intelligence on business. Foresight.

Nader, K., Toprac, P., Scott, S., & Baker, S. (2022). Public understanding of artificial intelligence through entertainment media. AI & society, 1-14.

Nell, V. (2008). Cruelty's rewards: The gratifications of perpetrators and spectators. Behavioral and Brain Sciences, 31(1), 23-24.

Ng, I.C., 2014. Creating new markets in the digital economy. Cambridge University Press.

O'Hagan, N., & Rooney, K. (2021). Understanding 5G: Perspectives on future technological advancements in media and entertainment. Convergence: The International Journal of Research into New Media Technologies, 27(3), 652-668.

Oliver, M. B., & Bartsch, A. (2010). Appreciation as audience response: Exploring entertainment gratifications beyond hedonism. Human Communication Research, 36(1), 53–81.

O'Neil, C. (2016). Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy. Crown.

Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. Foundations and Trends® in Information Retrieval, 2(1–2), 1–135.

Parsons, T. (1951). The Social System. Free Press.

Peter, J. P., & Olson, J. C. (2008). Consumer behavior and marketing strategy (8th ed.). McGraw-Hill.

Pham, M. T. (1998). Representativeness, relevance, and the use of feelings in decision making. Journal of Consumer Research, 25(2), 144-159.

Picard, R. W. (2003). Affective Computing: Challenges. International Journal of Human-Computer Studies, 59(1–2), 55–64.

Plutchik, R. (1980). Emotion: A psychoevolutionary synthesis. Harper & Row.

Prasetyo, P.E. and Dzaki, F.Z., 2020. Efficiency performance and productivity of creative industries. International Journal of Advanced Science and Technology, 9(6), pp.122-132.

Propp, V. (1968). Morphology of the Folktale. University of Texas Press.

Provost, F., & Fawcett, T. (2013). Data Science for Business. O'Reilly Media.

Reagan, A.J., Mitchell, L., Kiley, D., Danforth, C.M. and Dodds, P.S., 2016. The emotional arcs of stories are dominated by six basic shapes. EPJ Data Science, 5(1), pp.1-12.

Ritchie, T. (2020). Artificial Intelligence and the Media. Springer.

Rogers, E. M. (2003). Diffusion of Innovations (5th ed.). Free Press.

Ryan, M. L. (2018). Narratives in the Age of the Brain: Neuroculture, Neuropolitics, and the Complexity of the Self. University of Nebraska Press.

Salini Suresh, V Suneetha, Niharika Sinha, & Sabyasachi Prusty. (2020). Latent Approach in Entertainment Industry Using Machine Learning. International Research Journal on Advanced Science Hub, 2, 301–304. doi:10.47392/irjash.2020.106

Shapiro, C., & Varian, H. R. (1999). Information rules: A strategic guide to the network economy. Harvard Business Press. Zentner, A. (2003). Measuring the effect of file sharing on music purchases. Journal of Law and Economics, 46(1), 63-90.

Sharda, R. and Delen, D., 2006. Predicting box-office success of motion pictures with neural networks. Expert Systems with Applications, 30(2), pp.243-254.

Smith, G. (2018). The Emotional Arc: Digital Storytelling as a Tool for Impression Management. Springer.

Smith, G. D. (2019). Film Structure and the Emotion System. Projections: The Journal for Movies and Mind, 13(2), 119–136.

Snyder, B. (2005). Save the Cat!: The Last Book on Screenwriting You'll Ever Need. Michael Wiese Productions.

Sobchack, V. (1992). The Address of the Eye: A Phenomenology of Film Experience. Princeton University Press.

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer loyalty in e-commerce: An exploration of its antecedents and consequences. Journal of Retailing, 78(1), 41-50.

Sundararajan, V., Hollebeek, L., & Solnet, D. (2020). Customer engagement with augmented reality advertising: An exploration and conceptual framework. Journal of Business Research, 117, 631–641.

Tajfel, H., & Turner, J. C. (1986). The social identity theory of intergroup behavior. In S. Worchel & W. G. Austin (Eds.), Psychology of Intergroup Relations (2nd ed., pp. 7-24). Chicago: Nelson-Hall.

Tan, C. H. (2018). Artificial Intelligence in Cinema: Perspectives on Digital Storytelling. Springer.

Tan, E. S., Zillmann, D., & Taylor, K. (2013). Effects of anesthetic versus other forms of outcome resolution on curiosity and interest. Media Psychology, 16(3), 285–307.

Terry, D. J., & Hogg, M. A. (1996). Group norms and the attitude-behavior relationship: A role for group identification. Personality and Social Psychology Bulletin, 22(8), 776-793.

Theo, L. J. (2016). Considerations on conceptual frameworks for writing liminality into popular film. Journal of Screenwriting, 7(2), 155-172.

Thompson, K. (1999). Storytelling in the New Hollywood: Understanding Classical Narrative Technique. Harvard University Press.

Truby, J. (2007). The Anatomy of Story: 22 Steps to Becoming a Master Storyteller. Faber & Faber.

Turkle, S. (2011). Alone Together: Why We Expect More from Technology and Less from Each Other. Basic Books.

Van Laer, T., De Ruyter, K., Visconti, L. M., & Wetzels, M. (2014). The extended transportation-imagery model: A meta-analysis of the antecedents and consequences of consumers' narrative transportation. Journal of Consumer Research, 40(5), 797–817.

Varanasi Satyavan. (2019). Artificial Intelligence Vs Emotional Intelligence. Smart Moves Journal Ijellh, 7(11), 11–11. doi:10.24113/ijellh.v7i11.10103

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer experience creation: Determinants, dynamics and management strategies. Journal of Retailing, 85(1), 31-41.

Vieira, V. A. (2010). Rationality and emotion in consumer behavior: The case of hedonic products. Journal of Consumer Behaviour, 9(6), 424-432.

Vogel, H.L., 2015. Entertainment industry economics. Cambridge Books.

Vogler, C. (1998). The Writer's Journey: Mythic Structure for Writers. Michael Wiese Productions.

Vonnegut, K., 1981. Palm Sunday. New York: Rosetta Books LLC.

Vyas, N., Kumar, D., Jain, S., & Singh, A. (2019). Predictive maintenance: A survey. Journal of Manufacturing Systems, 53, 261-271.

Weninger, F., Eyben, F., Schuller, B., Mortillaro, M., & Scherer, K. R. (2013). On the acoustics of emotion in audio: what speech, music, and sound have in common. Frontiers in psychology, 4, 292.

Witte, K. (1992). Putting the fear back into fear appeals: The extended parallel process model. Communication Monographs, 59(4), 329–349.

Wright, E. O. (2000). Class Counts: Comparative Studies in Class Analysis. Cambridge University Press.

Wu, D., Aberer, K., & Datta, A. (2013). Sentiment analysis on social media streams. In Proceedings of the 2013 International Conference on Social Computing (pp. 1221–1226).

Yuan, Y., Kim, J. G., Shang, X., & Kim, C. S. (2019). Automatic Movie Scene Suggestion Based on Aesthetic and Cinematic Rules. IEEE Transactions on Multimedia, 21(3), 724-738.

Zackariasson, P., & Wilson, D. (2018). The video game industry: Formation, present state, and future. Routledge.

Zhang, X., Zhan, D., Chen, L., & Lu, H. (2020). Towards emotion-aware multimedia computing: A comprehensive survey. ACM Transactions on Multimedia Computing, Communications, and Applications.

Zhou, Y., Zhang, L. and Yi, Z., 2019. Predicting movie box-office revenues using deep neural networks. Neural Computing and Applications, 31(6), pp.1855-1865.

Zillmann, D. (1988). Mood management through communication choices. American Behavioral Scientist, 31(3), 327–340.

Zillmann, D. (2012). Transfer of excitation in emotional behavior. In A. R. Pratkanis, J. R. Turner, A. R. Pratkanis, J. R. Turner (Eds.), The Science of Social Influence: Advances and Future Progress (pp. 217–235). Psychology Press.