How do consumers percept Virtual Reality content? Focus on analyzing comments on the YouTube metaverse concert

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ABSTRACT

The live music industry has faced unprecedented challenges due to the Covid-19 pandemic, which has imposed severe restrictions on mass gatherings and social activities. As a result, many artists and fans have resorted to Virtual Reality (VR) technology as an alternative way of delivering and accessing live music content in a more immersive and interactive manner. Moreover, the idea of the metaverse has gained considerable attention as a possible model for organizing and experiencing live music events. However, with the gradual recovery from the Covid-19 pandemic and the return of on-site live concerts, it remains uncertain how consumers view and prefers VR concerts over traditional ones. This research enhances the understanding of the public opinion toward VR concerts and expanding the field of live music industry from the offline world to the online world by examining consumer data from YouTube, which is a relatively new source of information in the live music industry,

This research employs text mining techniques to scrutinize consumer data from YouTube to comprehend public opinions on VR concerts and their implications and difficulties in the post-Covid-19 pandemic era. The research gathers 10,298 comments from 5 VR concert videos and 27,529 comments from 37 general concert videos on YouTube. Specifically, the research utilizes TF-IDF word embedding and BERTopic topic modeling techniques to the unstructured data to ascertain the keywords and main topics in the comments. In addition, the text regression method is exploited to combine the unstructured data with structured data for deeper analysis. Moreover, the research contrasts how consumer opinions on VR concerts have shifted between 2019 and 2022 and how they diverge from those on general concert videos.

As a result, the research identifies 6 main themes comprising 11 dominant topics and 3 salient topics that encompass viewer behavior, the unique value of VR concerts, the advantages of VR concerts, and people’s perception of VR concerts as future modes of live concerts. The result of regression analysis further discloses public preferences by implicating the importance of artists in VR concerts and the fact that the interaction among audiences increases the engagement and sense of presence in the VR environment. Moreover, the research reveals that VR concerts replace live concerts under certain conditions and most viewers enjoy the visual stimulation of VR concerts. This research advances the understanding of telepresence in the context of a VR environment, contributing to the knowledge of how users experience and engage with VR content.

KEY WORDS: Metaverse; Virtual reality; Live music industry; Text mining; Word embedding; Topic modeling

TYPES OF THESIS: Application Research

CONTENTS

LIST OF ABBREVIATIONS

XR	Extended Reality
VR	Virtual Reality
AR	Augmented Reality
NFT	Non-Fungible Tokens
NLP	Natural Language Processing
TF-IDF	Term Frequency – Inverse Document Frequency
CBOW	Continuous Bag Of Words
LSTM	Long-Short-Term-Memory
ELMo	Embeddings from Language Models
BERT	Bidirectional Encoder Representations from Transformers
LDA	Latent Dirichlet Allocation
UMAP	Uniform Manifold Approximation and Projection
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
SBERT	Sentence-BERT
OLS	Ordinary Least Squares
VADER	Valence Aware Dictionary and Sentiment Reasoner
STD	Standard Deviation
NLI	Natural Language Inference
R.I.P	Rest In Peace
PSI	Positive Sentiment Index
NSI	Negative Sentiment Index

1 Introduction

1.1 Research Background

The worldwide spread of the Covid-19 pandemic has given tremendous restrictions to the world, such as keeping social distancing or restricting the number of gathering crowds to suppress the contagion of the virus. At the initial stage of the pandemic, all countries made policies to minimize death from the pandemic, and it varied from country to country (Béland et al., 2021). For example, the Chinese government tried to minimize intercity travel on national holidays, European countries locked down cities at the initial stage of the pandemic, and there were mass cancellations and postponements in U.S. sporting and cultural events.

To overcome these difficulties, there were new movements to bring the offline space into the metaverse. One of the key technologies of the metaverse, Virtual reality (VR), which is part of Extended Reality (XR), is used as the main method to provide an alternative reality for people (Han et al., 2022). VR gives an immersive experience with virtual content and space for consumers to interact and provides alternate ways to enjoy leisure without mass gatherings in the real world. This technology is used in various industries, such as in the education field, medical field, industrial field, and leisure field and its growth was dramatic during the pandemic. In addition, the world has been reopening its community since 2022, and it is crucial to understand the new types of consumer behavior that emerged during the pandemic at end phase of the Covid-19 pandemic. The main purpose of this research is to investigate if VR leisure can provide alternative choices for real-world leisure after the pandemic and in further future. In detail, this research explains how consumers think about VR concerts, comparing them to general concert videos and the possibility of their development by analyzing YouTube reviews on VR concerts.

1.1.1 Trend of Covid-19 and Situation of the Leisure Industry

Covid-19 struck the world since 2019, this virus has been mutated several times and gave new threats to the world over time. After 2022 omicron variant which has higher infectivity and transmissibility than the prior delta variant became the dominant variant of Covid-19. In the context of the leisure industry, the effect of the Covid-19 pandemic was huge and extremely severe. Restrictions from “Social distancing” to keep the virus been spreading violently in almost every part of the leisure industry. Mass gathering events were curtailed and almost banned worldwide at the peak of the Covid-19 pandemic even under hygiene research and practices to decrease the risk of transmitting Covid-19 (Moritz et al., 2021). These restrictions resulted in a huge economic impact on the leisure industry. In the tourism industry was greatly influenced. According to information from the World Tourism Organization In tourism (UNWTO), in 2020, 100% of worldwide destinations had restricted travel conditions, and international tourism arrivals dropped by 74%, translating into a loss of USD 1.3trillion (United Nations World Tourism Organization, 2021). This drop rate is the most considerable range in global tourism history after World War II (Kaczmarek et al., 2021). Similarly, in the live music industry, most companies had to cancel or postpone their events and the scale was unprecedented. According to a study, consumers spent 45% less on music each month than before the Covid-19 pandemic, especially live concerts and offline sales have hit the hardest (Denk et al., 2022).

In the situation of recession and constraints, information technology played a key role as the catalyst of leisure industries for their growth and sustainability (Xiang et al., 2021). For instance, filmmakers started to use robots and Augmented Reality (AR) visual images to keep social distancing during shooting the film. In the tourism industry as well, contact-free services using robots and internet of everything technologies were implemented. In addition to this, they tried to implement virtual tourism, and VR techniques for unique experiences and to keep their business without mass gatherings. Even in the live music industry where interaction with the audience and performers is regarded as one of the most important values, several companies planned concerts with the avatar of famous singers on a virtual stage.

After 2022, the omicron variant has reduced the severity of symptoms and provided material for researchers to improve the understanding of the mechanism and characteristics of Covid-19 variants (Fan et al., 2022). Furthermore, we have learned how to response to the pandemic from past and present pandemic cases, and when considering increased vaccination rates and infection rates, some researchers argued the world is ready to prepare to response to the virus more sophisticated way and return to the normal life in 2022 (Daria et al., 2022a; Ioannidis, 2022).

Following the research and predictions regards to the end of the Covid-19 pandemic and economic damage from long periods of constraints, numerous countries start to reopen their community, and borders and lift gathering restrictions. This movement can be clearly confirmed by research to track the policy of governments regarding the Covid-19 pandemic. According to the research of Hale, more than 400 volunteers from around the world have worked for collecting and coding the real-time data of pandemic policies with Oxford University (Hale et al., 2021). In the data of government policy part, they have 8 indicators of the government restriction policies, *School Closing, Workplace Closing, Restrictions on gathering size, Close public transport, Stay-at-home requirements, Restrictions on internal movements, Restrictions on international movements*, and scoring each of the policies by the intensity of it. As the data and Figure 1-1 show, the mean intensity of the government restriction of the world to the pandemic decreased significantly after 2022 when the omicron variant becomes the dominant variant of Covid-19. The long-term restrictions from Covid-19 are coming to an end and the world is recovering to normal life.

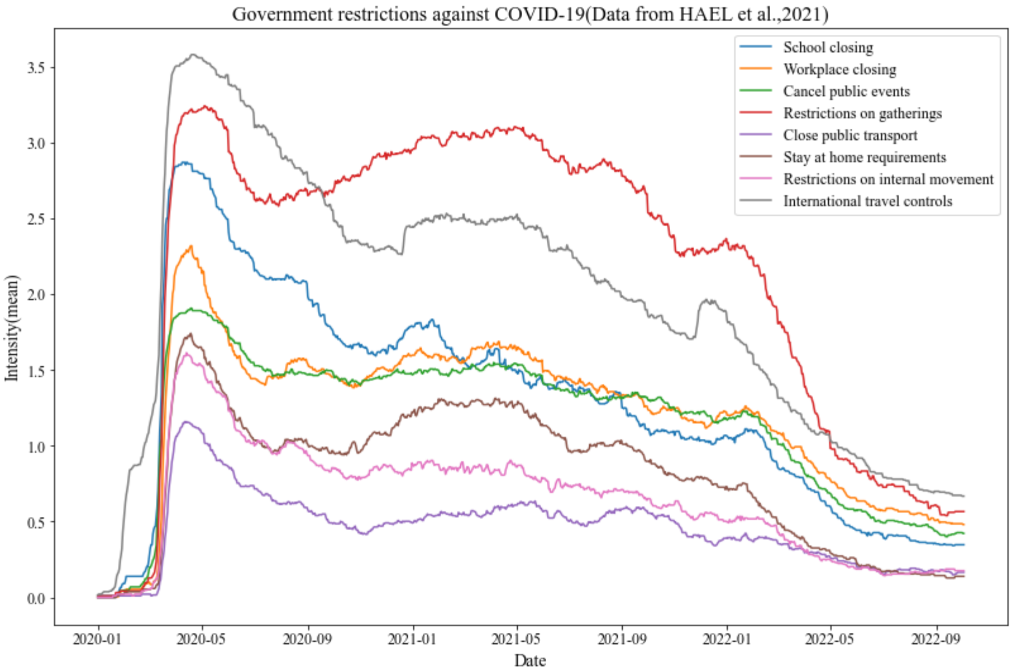

Figure 1-1 Government Restriction Polices Against Covid-19

The relaxation of limitations on large public gatherings and the global reopening that occurred after 2022 had a considerable effect on the leisure sector. In particular, there has been a remarkable recovery in ticket sales for live concerts and audience numbers. According to Live Nation Entertainment's 2022 second-quarter report, one of the largest global entertainment companies promoted more than 12,500 concerts during two quarters and saw a 20% increase in audience attendance compared to the same period in 2019 (Live Nation Entertainment, 2022). Additionally, 100 million tickets for 2022 shows were sold in the prior two quarters, exceeding the total number of fans counted in 2019. These figures surpassing pre-Covid-19 levels indicate that many people eagerly awaited leisure activities during the pandemic and this desire exploded as Covid-19 restrictions began to be lifted.

1.1.2 Introduction of Virtual Reality and Metaverse

There have been different definitions of Virtual Reality (VR) since it was first suggested. Most of the definitions refer that VR as the electronically simulated environment that can access by special hardware and software (STEUER, 1992a). VR has been kept developed today since it was first raised in the 1990s, made with its software to visualize the virtual environment, hardware making it possible to access the virtual world, like Samsung Gear or Oculus, and platforms operating the virtual world. One of the key directions that VR has been developed is the shape of online games, such as Second Life, VR Chat, and Fortnite. They mostly act as a platform of virtual worlds where consumers can interact with each other and immerse themselves in the virtual world. The recent advancement of information technology, infrastructure, and the outbreak of the Covid-19 pandemic accelerate the range of using VR and the importance of VR.

In 2021, one of the biggest Social Network Service (SNS) service providers, Facebook changed its name to Meta. CEO of Meta, Mark Zuckerberg batted their future on the metaverse.

He advocated that avatars would share our real daily lives, do shopping, do business, and enjoy leisure in the metaverse. Movement from Web 2.0 to Web 3.0 promising decentralization of ownership raised the concept of possession for digital property in the metaverse through cryptocurrencies and non-fungible tokens (NFTs) (Belk et al., 2022). These movements alter how certain businesses operate and create new opportunities for them. For instance, in the creative business, which is the economic activity to create the consumption of knowledge, content, and information such as artworks, music, movies, etc. this movement modified the relationship between buyers and consumers through smart contracts and NFTs (Malik et al., 2022) The classical concept of VR is rebranded with “Metaverse” and “Big Tech” that transform our daily life and will impact the way of business, marketing, leisure, and interaction (Dwivedi et al., 2022b).

Not only the concept of the digital property but also the advancement of visualization technology implementing virtual reality and new types of devices embodying the virtual world provide new kinds of experiences and uses in many industries (Dincelli et al., 2022). It has become possible to further reduce the gap between reality and virtual reality, and research and investment are actively underway accordingly. Furthermore, along with the breakout of the Covid-19 pandemic in 2020, VR could substitute many occasions by bringing real-world tasks into the metaverse to keep social distancing and quarantine. Despite this importance and development, the metaverse business is still a highly volatile area that has not yet been fully entrenched, and many companies are struggling to understand the metaverse business (Dwivedi et al., 2022a).

1.2 Problem Statement and Research Questions

Virtual Reality (VR) technology has been widely implemented across numerous industries and its applications are noteworthy. The market for VR is expanding rapidly, however, several challenges are presented at the same time (Morvan et al., 2020). For instance, it is still debatable whether VR can be a substitute for our daily life and efficiently replace part of real-world life (Xi et al., 2022). After the first quarter of 2022, it was anticipated that the spread of the Omicron wave would bring an end to the Covid-19 pandemic phase (Daria et al., 2022b). As a result, most offline activities have resumed around the world. Nonetheless, it remains uncertain whether VR concerts will retain their popularity as they did during the Covid-19 pandemic period. Despite this uncertainty, it is an established fact that VR content is more appealing compared to conventional content in specific fields (Flavián et al., 2019a). This is particularly evident in the leisure industry where VR-based content has experienced substantial growth during the pandemic.

Comprehending consumers’ responses to novel forms of leisure is becoming increasingly crucial. Although VR concerts gained immense popularity during the Covid-19 pandemic period, details regarding how consumers enjoyed and responded to these concerts remain obscure. At a time when conventional on-site live concerts resuming as communities reopen, it is imperative to examine the distinctiveness of VR concerts and conduct a comprehensive investigation into their current position and potential for future development.

The primary objective of this study is to investigate consumers' perceptions of Virtual Reality (VR) concerts and their uniqueness utilizing advanced topic modeling techniques. In detail, the research aims to examine current preferences for VR concerts and consumer perceptions by conducting a comprehensive analysis of over 10,000 comments on VR concert videos uploaded on YouTube to identify latent topics that interest consumers.

In addition, the study seeks to examine changes in consumer perception over time by comparing topical differences towards VR concerts from their inception in 2019 via the Fortnite platform to the gradual phasing out stage of the post-pandemic period after 2022. This provides valuable insights into how preferences for VR concerts have evolved over time, especially in relation to the Covid-19 pandemic, and enable us to make informed predictions about future acceptance by consumers. By investigating changes in consumer perception over time, we can gain valuable insights into the sustainability and future potential of VR concerts. Furthermore, this research aims to provide a deeper understanding of public opinion about VR concerts by comparing the topics of comments from all normal concert videos held before and after the Covid-19 pandemic. This will enable us to determine how opinions on VR concerts differ from those on general concert videos.

To achieve these objectives, the following research questions will be addressed:

(1) What are consumers' reactions to VR concerts as evidenced by their comments on YouTube videos of VR concerts held via the Fortnite platform?

- 10,298 YouTube comments data from 4 different VR concerts are used as the main data for the investigation. Those VR concerts feature their popularity and singers, viewers are all made in avatars.

- This thesis uses the Word embedding method to get the key features of comments.

- Topic modeling method to understand the latent topics of comments and categorize each comment into specific themes.

- Text regression method to further research public opinion.

(2) How have consumer perceptions towards VR concerts changed from their inception in 2019 via the Fortnite platform to the gradual phasing out stage of the post-pandemic period after 2022?

- Find out if there any difference on the consumer response before the Covid-19 pandemic and after the end of the Covid-19 pandemic.

- Concentrate on the topic difference from the first held of VR concert to the peak of the Covid-19 pandemic period and the gradual phasing out stage of the post-pandemic period.

(3) How do public opinions about VR concerts differ when compared with comments from general concert videos held before and after the Covid-19 pandemic?

- Used the comments from offline concert videos held after and before the Covid-19 pandemic to compare how people feel differently from general recorded concert videos and VR concert videos.

1.3 Significance of the Study

1.3.1 Theoretical Significance of the Study

Since before the 21st century, there have been several theories about how people feel and respond to stimuli in physically distant environments. Among them, the theory called Telepresence suggested by Minsky (1980) is used as the fundamental framework for writing this thesis. Telepresence refers to how to present one feels in a mediated environment rather than in their immediate physical surroundings (STEUER, 1992b). Steuer also defined virtual reality from the point of telepresence view as a real or simulated environment in which a perceiver experiences telepresence. Telepresence was later defined as three types in common use by Draper, and especially experiential definition of telepresence is mainly focused on in this paper.

In the experiential definition, telepresence represents a mental state in which users feel physically present within the computer-mediated environment (Draper et al., 1998). Draper suggests following experiential values, first, “Sense of Presence” that people feel a sense of being inside the virtual world. Second, “Immersion and Engagement” is about how individuals feel immersion and engagement in the virtual environment. With a heightened sense of realism and interaction, the person feels intensely absorbed and interested in the experience. Third, “Suspension of Belief” is estimating whether people accept the virtual environment as real despite being aware of its mediated nature. Fourth, “Engagement on an emotional and cognitive level” is the characteristic of a virtual condition that lets people participate on an emotional and cognitive level depending on the information and context.

This research is combined with the experiential definition of telepresence and offers scientific significance by deepening the understanding of the experiential qualities, changes over time, and comparative aspects of telepresence in the context of the VR environment by analyzing comments from YouTube VR concert videos. This understanding can inform the design, improvement, and optimization of VR concert experiences, ultimately enhancing user engagement and satisfaction in the virtual environment.

In-depth, first, the research can shed light on the subjective experience of presence, immersion, and engagement in the virtual concert environment by observing how consumers respond to VR concerts and examining their comments through the prism of the experiential definition of telepresence. This scientific contribution advances the knowledge of how users experience and engage with VR components by providing insightful information on the experiential elements that support the sense of telepresence.

Second, examining how consumer perceptions of VR concerts have changed from the post-pandemic period to after-pandemic period, within the context of telepresence, the study contributes to comprehension of the temporal dynamics of telepresence experiences. It gives the obvious proof on the effects of technological advancements, contextual factors, and evolving consumer expectations on the telepresence experience and offers perspectives on how consumer perceptions of presence, immersion, and engagement vary over time, particularly in response to the Covid-19 pandemic.

Third, by contrasting the public's perceptions of VR concerts with comments from general concert videos, this research can emphasize the distinctive features of telepresence experiences in VR concerts. It might bring perspective on how the immersive and captivating qualities of VR concerts, made possible by avatars and virtual settings, set them apart from conventional concert videos. This comparison attempts to clarify the experience characteristics that set VR concerts apart from traditional on-site concerts and make them effective for audience involvement.

Overall, this research advances telepresence research in the VR context. The research combined with the experiential definition of telepresence, contributes to advancing telepresence research specifically within the VR concert domain. By focusing on consumer reactions, changes in perceptions over time, and comparisons with general concert videos, the study expands the knowledge of how telepresence manifests and operates in the context of virtual conditions. This scientific contribution can inform future studies on telepresence, enhance theoretical frameworks, and guide the development of immersive technologies and virtual environments.

1.3.2 Practical Significance of the Study

In a practical sense, the research delivers valuable insights and suggestions that the VR concert business can put into practice to aid it to evolve, flourish, and align more effectively with customer expectations and preferences. First, it gives the consumers’ public opinion into the VR concert industry. By examining consumers' reactions to VR concerts through YouTube comments, the study provides informative insights into consumer opinions, preferences, and experiences in this emerging industry. Understanding consumers' reactions can help VR concert organizers, artists, and platform developers gain a deeper understanding of their target audience. This knowledge can inform decision-making processes related to content creation, marketing strategies, and user engagement techniques, ultimately improving the overall consumer experience and driving the growth of the VR concert industry.

Second, this research gives shifting consumer perceptions toward VR concerts. Investigating the changes in consumer perceptions from their inception to the post-pandemic period till the phasing out period of the pandemic contributes to the understanding of how the perception of this medium has evolved over time. This knowledge is crucial for adapting and refining VR concert experiences to meet changing consumer expectations, especially after the end of the Covid-19 pandemic. It serves to develop user engagement strategies, address potential concerns or barriers, and influence future innovations in the VR concert industry.

Third, this study demonstrates how consumer perceptions of VR concerts and traditional concerts differ. Specifically, comparing public opinions about VR concerts with comments from general concert videos provides practical insights into the unique aspects of VR concerts that distinguish them from traditional concert experiences. This analysis can help stakeholders in the VR concert industry understand the strengths and limitations of this medium compared to offline concerts. It can allow for more effective communication and engagement strategies tailored to the specific characteristics of VR concerts.

In short, the findings of the study, including consumer reactions, changes in perceptions, and differences between VR concerts and general concert videos, can offer practical guidance for strategic decisions in the VR concert industry. Understanding consumers' preferences, sentiment trends, and areas of improvement can help in crafting targeted marketing campaigns, optimizing user engagement, and enhancing the overall consumer experience. This knowledge can contribute to the successful promotion, adoption, and sustainability of VR concerts as an entertainment medium.

1.4 Research Structure

This research is conducted in six steps, and Figure 1-2 intuitively displays how it is organized. It is followed by:

Chapter 1: Introduction

This is the first chapter of the research explaining why this research is conducted and what will be dealt with throughout the whole research. Detailly, the research background has described the situation of the VR contents in recent days. With the understanding of the background, the recent industries’ problem has been stated, and then three research questions are suggested to investigate the problem in detail. Finally, how this thesis gives the theoretical and managerial implications was depicted.

Chapter 2: Literature Review

The second chapter of this thesis aims to understand the live music industry by describing consumer patterns in traditional live concerts and live concerts in the digitalized era, with a purpose to expand the concept of value into VR concerts It then studies how live music is developing in a virtual reality environment. Finally, it explores how the methodology that is judged to be the most appropriate for achieving the goal of this thesis is being exploited.

Chapter 3: Research Methodology

The research methodology chapter describes previous studies related to Natural Language Processing (NLP) and suggests the NLP model selected as the main methodology for the research. Specifically, it presents the Research Framework on how to conduct research using the corresponding NLP techniques. Then, it explains how NLP is currently evolving and in which areas it is being used. It also introduces the characteristics and representative algorithms of Word Embedding, one of the methodologies of NLP, and TF-IDF word embedding model which is the main model used in this research. Then, it explains one of the recent methodologies of NLP, Topic Modeling, and suggests representative algorithms and main models. Finally, the development regression model using unstructured data with structured data is explained and make hypotheses.

Chapter 4: Result and Discussion

Chapter 4 describes the data collection methods and key findings of this study. In particular, this research details the data collection method and the pre-processing steps of the unstructured text data. It also explains the data through the figures and characteristics of it, crucial keywords extracted with the TF-IDF word embedding model and compares them with separated classes divided by the form of concert videos. Finally, we discover meaningful latent themes of embedded comments through the BERTopic model. In addition, it explains how themes change over time and states how they differ from regular concert videos.

Chapter 5: Conclusion and limitations

The final chapter of this research summarizes the whole contents of the findings done in previous chapters. After, the study is concluded by describing the limitations of this thesis and the direction of future research related to the subject.

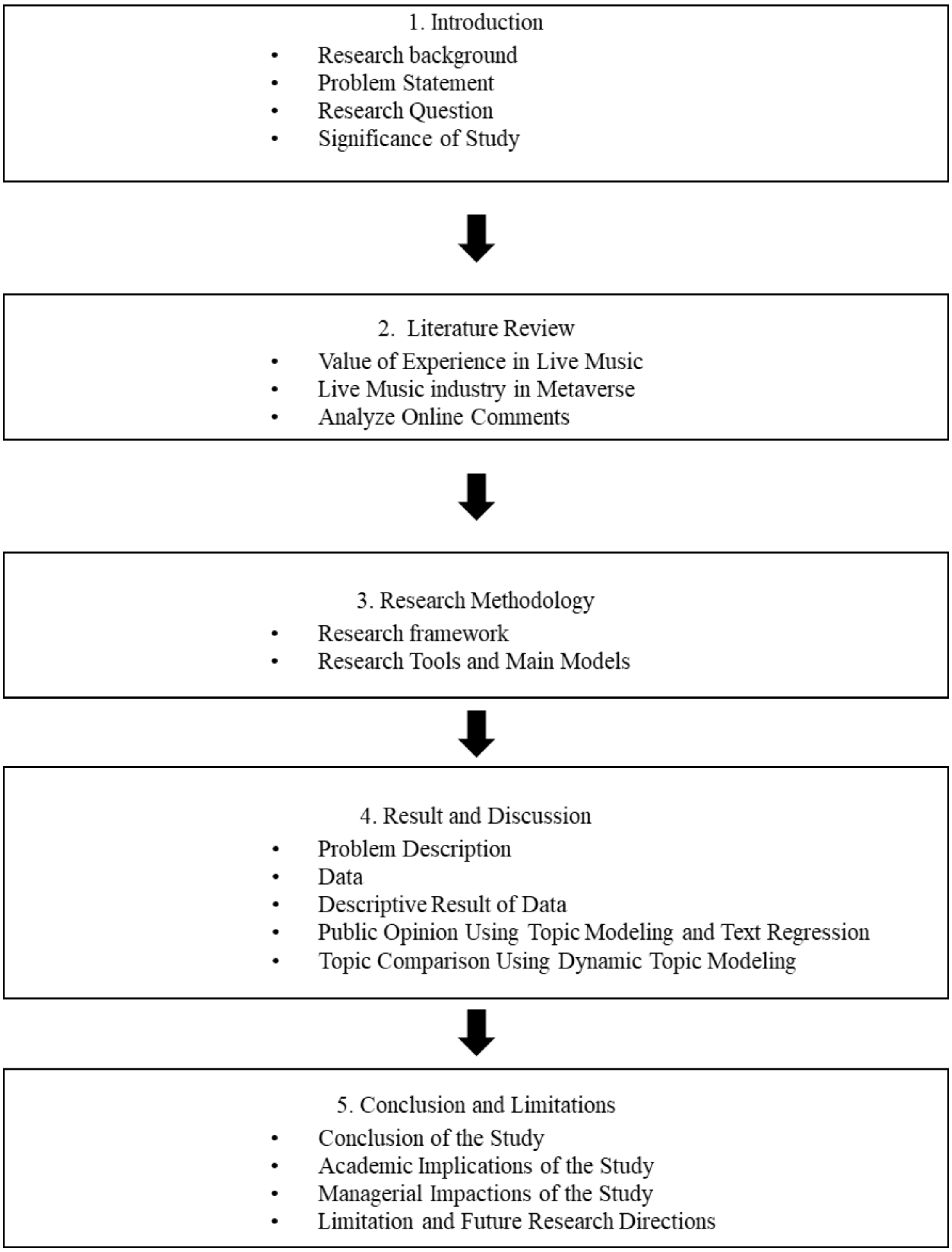

Figure 1-2 Research Structure of This Thesis

2 Literature Review

This chapter explains the previous literature relevant to the main research direction of this thesis. First, this study examines the value of live music in traditional on-site concerts and digitized environments, respectively, in order to find how this value can be applied to VR concerts. In addition, by studying the situation of the live music industry along with the metaverse, previous studies were developed with the specified research direction. Final, the application method of the methodology mainly used to achieve the purpose of the study was investigated, and an appropriate model was selected based on prior research.

2.1 Value of Experience in Live Concerts

In the era of Marketing 3.0, the way of consuming music was not just owing or listening to songs, but new types of consumers. Music Audiences 3.0 tend to enjoy the interaction between performers and attendance, and pursue the value of experience, which is the end product of live music (Charron, 2017). Specifically, Brown et al. (2017) surveyed 249 participants and found that the important experiential values of live music events were *"being there"*, *"proximity of artists"*, *"visual stimulation"* and *"social interaction"* (Brown et al., 2017). "*being there*" is the value that participants can feel the uniqueness of the event and can feel the atmosphere of the live concert. "*proximity of artists*" is the definition that participants can be close to the performer physically, for example, listen to their live performance just in front of them and sometimes shake hands with them. Also, psychologically feeling the musicianship of performers is also a value of it and that refers to the relationship between fans and artists. The visual element is also one of the great values of live music, which is generally made up mainly of visual stimulation to the stage setting. Finally, "*social interaction*" is a value that defines the joy of participants feeling and enjoying the atmosphere of the venue together.

However, the digitalization of live music brings changes to the ecosystem of the live music industry and the value of experience is reconfigured (Zhang et al., 2021). In the research of Zhang et al. (2021), they argued that live music easily becomes a digital archive since recording and uploading are faster than before and so the "liveness" of the content is diluted. Therefore, the experience of participating in a "real-time" event rather than the presence of "real space", became more valuable to customers in the live music industry. Furthermore, after the Covid-19 pandemic, most live performance events inevitably turned to online alternatives because of the lockdown and the live-streamed concert was the best alternative for musicians and event producers. The empirical result of questionnaires with 294 participants conducted by Areiza-Padilla et al. (2022) gives great implications regarding the online concert (Areiza-Padilla et al., 2022a). They argued that they could find the emergence of new consumers who positively value online concerts in the context of Covid-19. In detail, they confirmed that consumers were satisfied with online concerts during the Covid-19 pandemic, and if the quality of online concerts meets the expectation of viewers, they are willing to enjoy online concerts in the future. In addition to this, Swarbrick et al. (2021) compared the social connectedness and "*kama muta"* of live streaming and pre-recorded video through the survey of 299 participants. *Kama muta* in this research represents the warm, positive emotion so viewers can feel a connection to the music through empathy or its rhythm. They found that the liveness of video significantly affects social connectedness, however, it doesn't affect the *kama muta*, which can be interpreted that viewers can feel common empathy and can enjoy the recorded live performance together (Swarbrick et al., 2021). The experiential values of live concerts are being filled in various ways with the development of technology, and it is necessary to extend the experiential values of live concerts into the digital context, especially after Covid-19.

2.2 Live Music Industry in Metaverse

The emergence of metaverse has had a significant impact on the live music industry with novel visual experiences and has become a huge hit (Jin et al., 2022). Especially, one of the key technology, VR is considered as the key factor for the future of the live music industry by some researchers (Baía Reis et al., 2022; Wilson, 2021). Baía Reis et al. (2022) emphasized the characteristics of virtual reality that can ignore the physical laws of the real world. Event producers can plan the event with creative unlimitedness that can make the stages for venues graphic and performative boundless that embodies and controlling virtual avatars or featured interactions which are impossible in the real world. Wilson (2021) claimed that the advent of developed VR technology extends the way of *"seeing"* performance to the way of *"seeing"*, *"feeling"* and *"being"* of performance since they provide an immersive experience to consumers. Moreover, online channel, one of the main streaming channels of the VR concert, has the great potential to be an effective medium for increasing access to cultural event and overcoming some of the restrictions that limit live cultural participation, such as high prices and time constraints (De La Vega et al., 2020)

Following the importance of VR, the effectiveness of VR is also confirmed by previous research. It was revealed that VR strengthens the sense of presence when enjoying the content compared to normal 2d content (Elsey et al., 2019), enhancing the consumer experiences when they enjoy leisure (Flavián et al., 2019b). Onderdijk et al (2021) did experiments to determine the level of social connectedness of live-streamed concerts with 83 participants. As a result, viewers with VR glass feel more physical presence than viewers watching normal YouTube Livestream, and viewers can feel social presence by interacting with other viewers and chatting with each other in online condition (Onderdijk et al., 2021). One of the interesting approaches made by H. Kim et al (2021) is that they compare two independent period samples, pre-, and post- Covid-19 pandemic, to find out the effect of VR experiences on the attitude changes and visit intentions of tourism in the context of the Covid-19 pandemic. With the survey of the pre-Covid 19 groups (n=250) and post-Covid-19 groups (n=260), they demonstrate that VR plays a critical role when choosing tourist destinations after the Covid-19 pandemic (Kim et al., 2021). However, depending on the condition and context of the VR content, it sometimes gives negative sentiment to the consumers (Slater et al., 2022). In detail, Slater et al (2022) conducted experiments with 51 people to understand the responses of participants to different scenarios of VR concerts. The result of their experiments indicates that when people illusion that the situation is happening even if it is in a VR condition, the abnormal situation of VR concerts causes negative emotions in them. Therefore, VR is still a double-edged sword technology and requires a deeper understanding of consumers' reactions to it.

2.3 Applications for Analyzing Comments Data

The history of the live concert via YouTube is not short, and social platforms like Twitter or Facebook served as a channel for communication between fans and made them feel like they were experiencing a "live" concert even if they didn't physically go there (Bennett, 2012). After the Covid-19 pandemic, most concerts were held digital-way and it was discovered that the comment of the concert is an important factor as it leads to the positive impression and sustainability of online concerts (Areiza-Padilla et al., 2022b). Through the result of explorative analysis with 1,501 comments on recorded concerts video, Vandenberg et al (2021) revealed that viewers share moods and feelings with words and emoji, so they can feel socially connected. On the other hand, they also found some of the viewers feel a sense of physical isolation and consider it just as a recorded video, not a live music concert (Vandenberg et al., 2021). When considering the different results from some research, it is important to clearly understand the opinion of consumers enjoying live performance through digital conglomerates.

One of the most efficient ways to understand the response of the public is to analyze dominant opinions from textual data from social media using machine learning and natural language processing algorithm (Ghani et al., 2019). Especially, several research already showed that adopting the NLP techniques to YouTube comments give us insightful result to understand public opinion. The research of Feng et al (2019) exploited data mining and text classification with 20,149 YouTube comments supporting that it is very useful for understanding the overall attitudes of consumers to the content of video academically and managerially (Feng et al., 2019). Zheng et al (2021) also could extract the changing dynamics of public opinions and interest regarding Covid-19 using 46,732 comments data from daily briefings from the Canadian prime minister (Zheng et al., 2021).

2.4 Research Gap

This research contributes to the prior literature in three distinct ways. Firstly, it introduces a novel dimension of experiential value associated with live music concerts. While prior research has primarily examined consumer responses to conventional on-site live concerts or general concert videos, this study acknowledges the unique characteristics of online VR concert videos, which combine VR technology with the immersive experience of live music performances. By investigating the consumer reactions to this specific form of VR content, the study redefines the value proposition of live music concerts within remote conditions and virtual environments.

Secondly, the research explores the dynamic nature of consumer perceptions regarding VR concerts over time. Although some researchers have investigated the consumer experience of live concerts or live-streaming videos, no prior study has examined how consumer sentiments towards VR concerts may evolve over different periods. Given the availability of the publication year of YouTube comments, this thesis intends to divide the comment data into three distinct periods: pre-Covid-19, Covid-19, and post-Covid-19. This temporal distinction will provide valuable insights into whether consumer preferences for VR content have undergone significant shifts as the Covid-19 restrictions gradually diminish.

Another research gap lies in the methodological approach used to capture consumer responses to VR content. This thesis uses a distinct type of dataset—more than 30,000 comments from YouTube—to analyze customer preferences and sentiments, in contrast to much of the preceding literature, which primarily depends on survey-based approaches to acquire consumer opinions. There is a research gap in understanding the preferences and reactions of people in this online context, especially considering the increasing prevalence of online concerts, particularly in the occurrence of the Covid-19 outbreak. By utilizing a significantly informative dataset from online VR concert videos, this thesis seeks to fill this gap by offering insightful details about viewer preferences and experiences, particularly in the post-Covid-19 period. This study deepens the understanding of how consumers react to VR content across a variety of dimensions by utilizing cutting-edge Natural Language Processing (NLP) approaches. This is the first academic study to examine how consumers value VR leisure experiences using NLP techniques on such a sizable comment dataset.

In summary, this thesis addresses significant research gaps in the existing literature on consumer reactions to VR content in the leisure industry, particularly within the live music sector. By exploring the unique value of VR concerts, investigating temporal changes in consumer perceptions, and employing advanced NLP techniques on a large-scale comment dataset, this research contributes to a more comprehensive understanding of how consumers respond to and engage with VR technology in leisure settings.

3 Research Methodology

Chapter 3 includes particular explanations of the process of this research. The Research Framework initially outlines the stages involved in conducting this study and the primary techniques used to produce its findings. Then, the primary technique and tools are introduced with descriptions, concepts, and representative models.

3.1 Research Framework

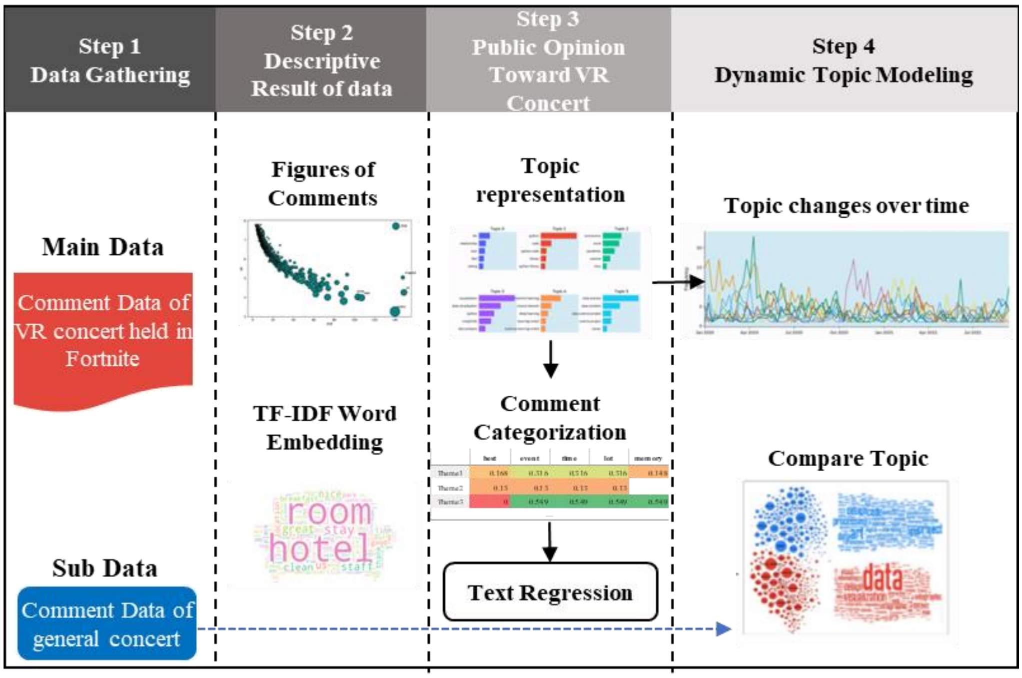

Figure 3-1 Framework of the Research

The main objective of this research is to investigate the public preference for VR leisure, specifically focusing on the live music industry, by analyzing comment data from YouTube. The research framework is closely linked with the experiential definition of telepresence, which refers to the feeling of being present in a virtual environment and experiencing events as if physically present. By examining the comments from VR concert videos held in Fortnite, as well as general concert videos before and after the Covid-19 pandemic, this study intends to investigate more about the mental state of experiential aspects of telepresence in VR concert.

In Step 1 of the research framework, Python and the Selenium library are employed to gather YouTube comment data. To ensure data accuracy, a data preprocessing process is conducted to enhance the analysis and comprehension of the data. In the next step, a descriptive analysis of the collected data is performed. This includes tracking the number of comments over time, categorizing them by singers and types of concerts, identifying the most empathetic comments among viewers, and extracting key terms using a word embedding model. This step provides a detailed understanding of the data and sets the foundation for subsequent analysis.

In Step 3, the topic modeling method is applied to uncover the current public opinion of VR concerts. It presents perceptions of the salient elements and facets of the VR concert experience that appeal to viewers. Analyzing the topics and themes can make it considerably clearer to identify factors that enhance the experiential value of telepresence. Additionally, a quantitative analysis of the comment data is conducted by employing text regression techniques. This analysis aims to reveal relationships between key terms, such as those represented by dominant topics, and numerical values, like the number of likes, sentiment index of comments, and the year of publication of comments. This approach facilitates a deeper understanding of the data by combining topic modeling results with specific analytics that can differentiate between classes or correlate with numerical values.

Finally, in the last step, the research focuses on investigating the differences in comments based on various characteristics using dynamic topic modeling. This step examines the changes in topics over time, particularly distinguishing between the peak of the pandemic period (from 2020 to 2021) and the gradual easing of the pandemic (after 2022). Further comparison is made between the topics of comments from general concert videos before the Covid-19 pandemic (from 2018 to 2019) and the later stages of the pandemic (from mid-2021 to 2022) with those of VR concert videos. This step enhances the contributions to understanding the distinctive experiential value of telepresence in VR environment. It could figure out how the perceptions and preferences of viewers for VR concerts have changed in reaction to changing circumstances by evaluating the shifting in topics across time and differentiating between different periods. The results of this evaluation allow for whether viewer themes, sentiments, or priorities have changed, delivering important information into how the pandemic has affected the telepresence experience. Moreover, comparing the topics of comments from general concert videos before and during the pandemic with those of VR concert videos allows for a comparison of the unique aspects of telepresence and how it differs from traditional concert experiences. This comparison supports highlighting the exceptional experiential value that telepresence in VR concerts delivers, such as a sense of immersion, interactivity, or novel features that improve the overall concert experience.

Figure 3-1 shows the framework of this thesis. The research framework aims to explore the public preference for VR leisure in the live music industry by leveraging comment data from YouTube. By aligning with the experiential definition of telepresence, the study seeks to uncover the subjective experiences and opinions of viewers, providing valuable insights into the immersive nature of VR concerts and their impact on the overall consumer experience.

3.2 Research Tools and Main Models

3.2.1 Natural Language Processing (NLP)

Today, most of the data is organized with unstructured data, which means that data is made for human consumption rather than for machine consumption. For daily use, it is convenient and intuitive for us, however, for developers who want to organize, modify or analyze this unstructured data it is almost impossible to interpret it since they have to use a machine. To solve this problem, many researchers have found ways to make it possible and Natural Language Processing (NLP) is one of the concepts for making machine deal with text data (Hirschberg et al., 2015). NLP is used in various fields, from basic technologies such as machine translation, speech recognition, and speech synthesis. Further, researchers developed these technologies for practical applications, for example, data mining from social media, sentiment analysis to understand the customer's emotion toward products and services, topic modeling, and auto-answer application for the inquiries of customers. In this research, I used word embedding techniques and topic modeling belonging to NLP. In short, word embedding technology is the way to vectorize words to make the computer understand human words and topic modeling is the technology to find the latent semantic components from documents or comments.

3.2.2 Word Embedding

Word embeddings are a type of word representation that connects meaningfully human and machine understanding of knowledge. A group of real numbers (a vector) could serve as the representations in word embeddings. In other words, word embeddings are sporadic representations of a text in *n*-dimensional space that aim to convey the meanings of the words. Recently, word embeddings are one of the most widely used applications of unsupervised learning since they do not need expensive annotation. According to the literature review, word embedding could be separated into three types with the method of transforming the words into vectors (Selva Birunda et al., 2021). In detail, first, Count vector, Term frequency-inverse document frequency (TF-IDF), and Co-occurrence are the category of Frequency-based word embedding, second, Word2vec, Glove, and FastText are the category of Static word embedding, and finally Embeddings from Language Models (ELMo), GPT-2 and Bidirectional Encoder Representations from Transformers (BERT) are the categories of Contextualized word embedding.

In the early days of word embedding technology, traditionally it was based on the frequency of whole documents and tried to discover the significant unique word, count the numbers of words, and co-occurrence of words. One-hot encoding is a basic transformation technique in which each word defines one dimension and the binary value (1 or 0) denotes the word's presence or absence. This encoding simply transforms the words into numbers, which means that vectorized numbers do not have any information about the relationship between the words and the context of the sentence. TF-IDF, on the other hand, can represent how relevant a word is to a document. TF-IDF is divided into two processes, term frequency (TF) which counts word frequency in documents, and inverse document frequency (IDF) which assigns weight to the words with their occurrence in documents. The intuition is that a word that occurs in many documents frequently like "of", and "a" are not important so gives less weight than other terms which occur in a few documents and this give robotics result for analyzing the text data (Robertson, 2004).

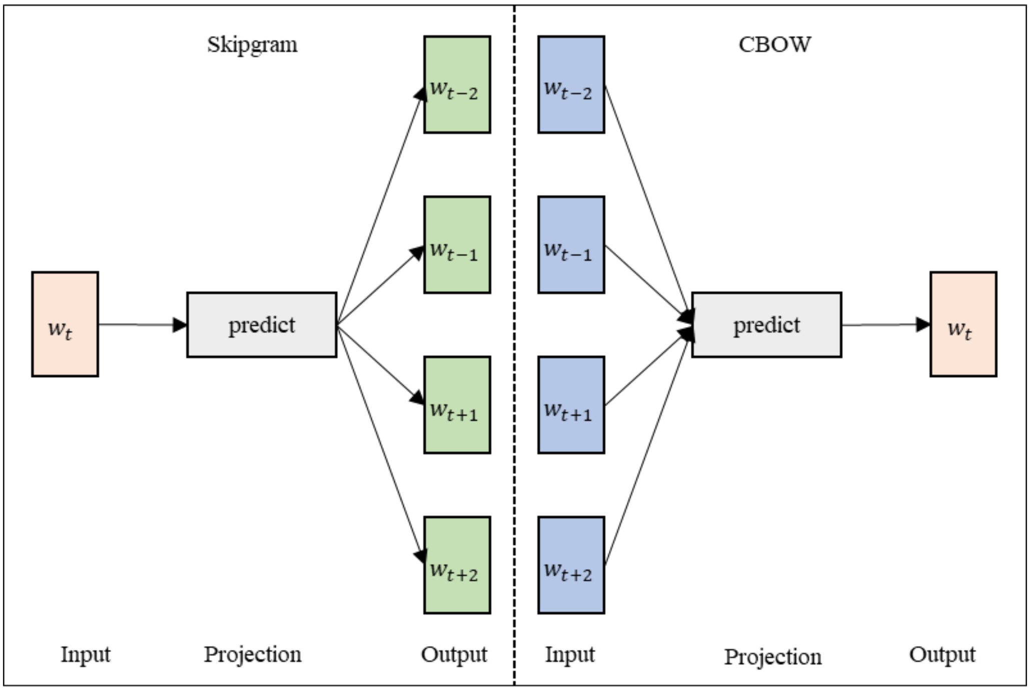

Figure 3-2 Representation of the CBOW model and Skipgram model

The prediction-based technique known as static word embedding converts each word into a vector and assigns a probability to them with the spatial position of the word vector. The probability comes up with training large textual data and since this trained data is not changed, it is called static word embedding. Word2vec is one of the most popular and successful ideas of static word embedding proposed by Mikolov (Jang et al., 2019). Word2vec has two separate methods to train the text data called Skipgram and Continuous Bag Of Word (CBOW), both methods using neural networks. Figure 3-2 shows the mechanism of both models and this looks like the flipped flow of each other. In the Skip-gram model, the distributed representation of the word is used to predict the context (surrounding words of *w*). On the other hand, for the CBOW model, the distributed representation of context (surrounding words of *w*) is used to predict the word in the middle of the context. Fast text is the other example of static word embeddings suggested by Bojanowski et al. from Facebook (Bojanowski et al., 2016). The key concept of FastText different from Wrod2vec is that it breaks words into several characters (or n-grams) and then inputs them into the neural network model. For example, in FastText when taking 3 grams, the word *"where"* is broken to <*wh*, *whe*, *her*, *ere*, *re*>, and the sum of representation vectors of characters represents the one word. Therefore, FastText can compute the word which was not included in the training text data.

Although static word embedding brought great advances in the NLP field, it still has a limitation with representing the polysemous word since each word shares one vector. Given this problem of static word embedding, recent works tried to capture the word semantics in different contexts and this concept is called contextualized word embedding. ELMo and BERT are milestone models of contextualized word embedding. These two models outperform compared to static word embedding in a performance like concept extraction from text data (Si et al., 2019). Figure 3-3 shows the Word Embedding flow of ELMo. ELMo first trains the sentences with a language model using a bi-directional Long-short term memory (Bi-LSTM) to learn the forward and backward of sentences. Then ELMo draws out the contextualized embedding way of concatenating hidden states (including initial embedding), multiplying each vector by a weight depending on the task and summing the vectors. BERT is the Transformer based model and uses the attention mechanism. Attention in NLP is the method to determine the relationship between words in a given sentence. Since BERT is a bi-directional model, the left and right context of given words is checked to represent the word, which means that a single word can have different embeddings following context.

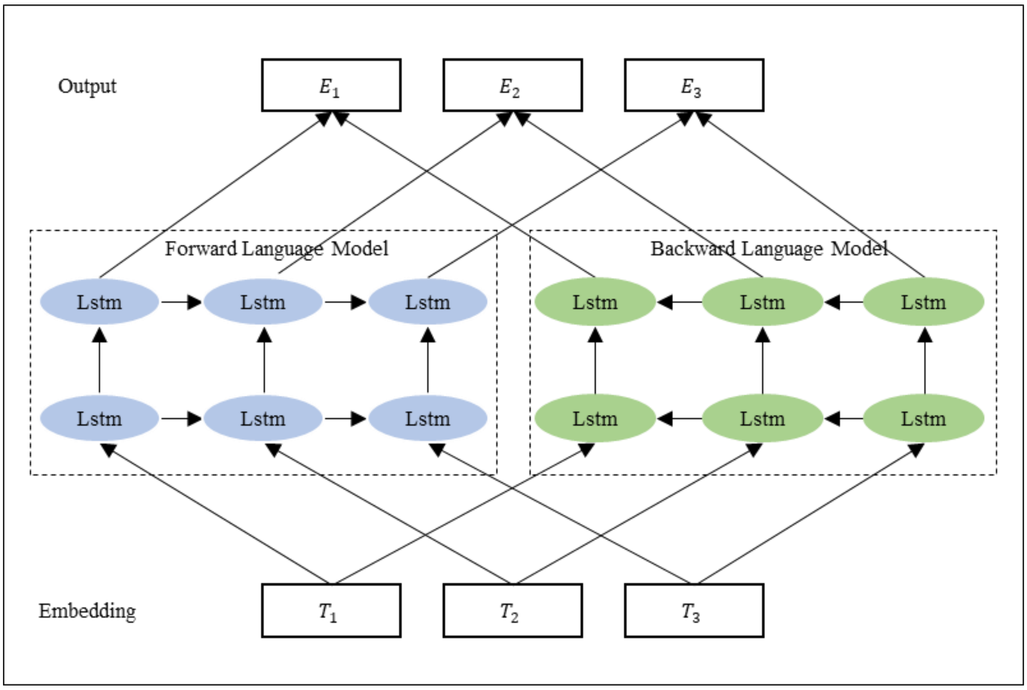

Figure 3-3 Word Embedding Process of ELMo

3.2.3 TF-IDF Word Embedding

In this research, TF-IDF is used as a main word embedding model to find meaningful keywords from the distribution of comments on VR concerts. By counting word frequency, I can get the qualitative result of the data and broad insight about the data before extracting the topic from whole comments. Especially, since TF-IDF models can reserve statistical information of data by exploiting term weighting related to documents, it has an effective algorithm to extract the key term from text data (Chen et al., 2019). TF-IDF has two steps to get the word embedding which is Term Frequency and Inverse Documents Frequency.

(1) Term Frequency (TF): Term Frequency step is to count the number of terms present in documents.

$$tf(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \tag{3-1}$$

Where $f_{t,d}$ is the number of term or word (t) that appears in the document (d), comment in this research, and divide it by the total number of terms (t') in the document (d). Simply it is counting the number of the specific term from whole terms in documents.

(2) Inverse Document Frequency (IDF): Inverse Document Frequency is the second step of the TF-IDF model. In the first step of TF, it simply calculates the number of terms, and can be observed it treats all terms in equal weights. If we just use TF for word embedding, some meaningless terms such as "of", and "a" will be regarded as important keywords. However, all words have different weights and IDF measures the importance of terms in whole data by tracking if terms are common or rare. IDF calculates the proportion of documents in text data that contains the term.

$$idf(t) = \log \frac{N}{1+df(t)} \tag{3-2}$$

$$idf(t) = (\log \frac{1+N}{1+df(t)}) + 1 \tag{3-3}$$

Where N refers to the number of documents, or comments (d), in the corpus (D), or text data, and the denominator $df(t)$ is the number of documents in the corpus that contains the term (t). If the term is not in the corpus, the denominator will be zero, which has a mathematical error, so it is common to adjust the denominator to $1 + df(t)$. Finally scale the value with the log to get clear output from a wide range of counts, since the corpus normally has a huge amount of data, and documents as well. In the "*TfidfVectorizer*" from the Python library scikit-learn that I used, it utilizes a smoothing technique that adds constant 1 to the numerator and denominator as IDF has an extra document that contains every term in the corpus exactly once and can prevent the zero denominators. Also, it adds 1 to avert terms with zero IDF value being ignored when calculating Equation (3-3).

(3) Term Frequency–Inverse Document Frequency (TF-IDF): Through two steps, we can get the TF-IDF score of a term by multiplying TF and IDF. Intuitively, the higher the score, the more important the words have in the text data.

$$tf - idf(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} * \{(\log \frac{1+N}{1+df(t)}) + 1\} \tag{3-4}$$

3.2.4 Topic Modeling

When humans read documents, it is easy to understand the concept and content of the document. In the sense of data, understanding the document is to determine the characteristic of unstructured data, text data. Topic modeling is a way researchers use programs to capture latent variables in text data. Along with the rapid digitalization of our economy and the availability of big and unstructured data, topic modeling techniques are utilized in extensive fields academically, practically and in diverse application domains (Reisenbichler et al., 2019).

Latent Dirichlet Allocation (LDA) developed by Beli et al. is the early and still frequently used topic modeling method. In LDA, the topic is a probability distribution over words and so LDA is probabilistic topic modeling. LDA is also a generative model in that the topic is generated first with relevant terms and then observed documents are generated from the distribution of topics (Blei, 2012). Figure 3-4 shows the graphical steps of LDA to generate the document by identifying topic distribution and word distribution. In detail, first, topic distribution (θ) is generated with Dirichlet distribution vector value α. Second, word (ω) is generated by topic (z) chosen from topic distribution (θ) and then the term for each topic is sampled from word distribution (β) with the words according to the chosen topic. By iterating these steps, LDA attempts to evaluate the topic distribution and word distribution to disclose the latent structures.

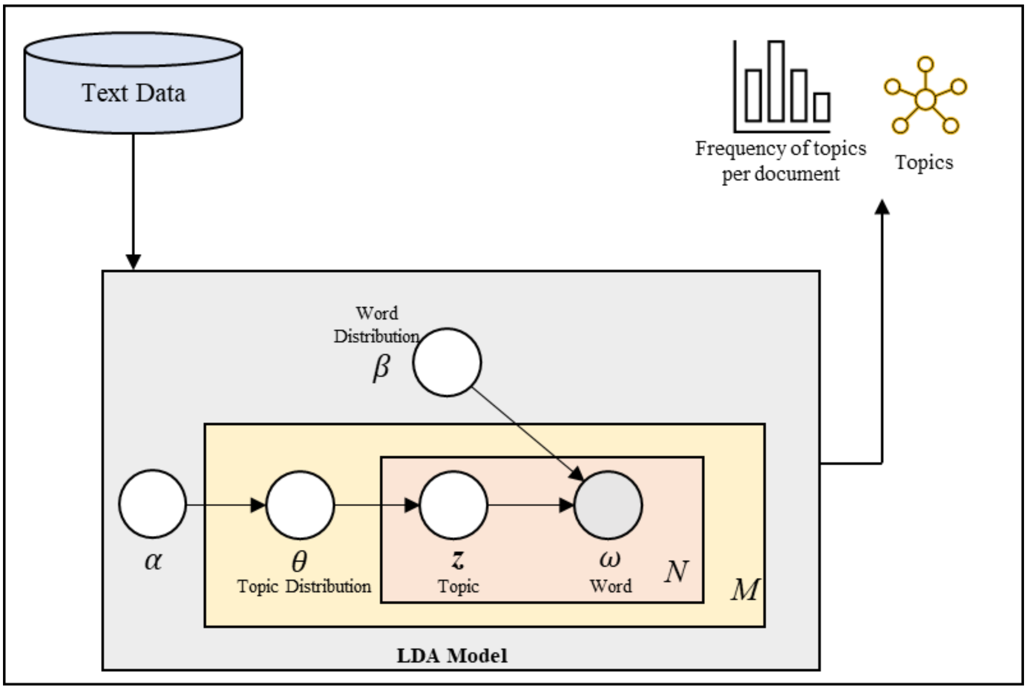

Figure 3-4 Graphical Model Representation of LDA

LDA was used long and widely among researchers and they have made great achievements with it. Nevertheless, in the case of short text such as comments from Twitter, YouTube, and Instagram, it is not the ideal model to extract the topic for those kinds of text data (Vayansky et al., 2020). Top2Vec and BERTopic are relatively new and similar algorithms to extract topics from text data by using word embedding and text clustering (Egger et al., 2022). The essential concept of those algorithms is that first, pre-trained embedding models are used to create the word and document embeddings that make it possible to locate semantically similar words, sentences, or documents in vector space. Then, to reduce the sparsity of the vector space, dimension reduction is conducted. Finally, the word vectors that appear closest to the document vectors are assigned as the topic of the document and the number of documents clustering together represents the number of topics. BERTopic has a difference for using class-based TF-IDF that considers the importance of a term within a cluster and creates the term representation.

3.2.5 BERTopic

BERT, developed by Google is considered the model that brought the revolution of NLP research (Egger, 2022), and BERTopic is the topic modeling method to find the latent topic utilizing this revolutionary contextualized word embedding. BERTopic is a relatively new model, that was developed in 2021, but its usefulness and accuracy have already been proven in some research (Sánchez-Franco et al., 2022). Also, some of the features of BERTopic are suitable for this research that BERTopic has better performance to get topics from short text and YouTube comments in this research. Moreover, BERTopic supports dynamic topic modeling and smoothing technique that provides a way of class-based topic modeling and the topic changes over time which can compare the topic between different classes of data. BERTopic extracts topics through 3 steps. First, it uses Sentence-BERT (SBERT) framework developed from BERT to vectorize documents to compare semantic similarities among whole documents. Second, to optimize the document clustering process, it uses Uniform Manifold Approximation and Projection (UMAP) to reduce the dimensionality of document embeddings and cluster them with Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN). Lastly, with the clusters of documents, topics are extracted by utilizing a class-based variation of TF-IDF.

(1) Encoder of Transformer model: The transformer model suggested in 2017 is the baseline architecture for advanced contextualized word embedding connecting the encoder and decoder with the attention mechanism (Acheampong et al., 2021). The encoder of the Transformer is organized with *N* stacks of layers, and the authors used 6 stacks in their article. Each layer has 2 sub-layers: the multi-head of self-attention mechanism, and the fully connected feed-forward neural network.

The first layer of the encoder, “Attention” is the mechanism suggested to help improve the performance of the machine translation function that enables the model to concentrate on the relevant parts of the input sequence depending on the task. The first step of the attention model is to take embedded words of input sentences to produce attention-based representations: $A(q, K, V)$ q for queries, K for keys, and V for values. Before producing the representations, the model adds a patterned vector to each input embedding to determine the position of each word or the spatial difference with other words. These representations are produced by multiplying input embedding with three matrices that are updated through the training process. The second step is needed to calculate the score of self-attention with representations. Equation (3-5) shows how to calculate an attention score of a single word. In advance, taking the dot product of the query vector (q) of the word and key vectors (k^i) of other words, compute the Softmax over them, then multiply it with the value of the word (v). Finally, by summating all the values from the prior calculations, the score of the word is computed. The score settles the most relevant key vector of other input words with the calculating query vector. Equation (3-6) is a compressed and vectorized representation of Equation (3-5). The denominator $\sqrt{d_k}$ is for scaling the dot product that leads to more stable gradients and they called it Dot-product attention in the study.

$$A(q,K,V) = \sum_i \frac{\exp(q \cdot k^i)}{\sum_j \exp(q \cdot k^j)} * v^i \tag{3-5}$$

$$A(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}}) * V \tag{3-6}$$

In the study, the authors developed a self-attention layer through the mechanism called multi-head attention. Multi-head attention considers every single attention as a head of attention and calculates the *i* different single attention, 8 is assigned for *i* in the article, which means that this layer has 8 heads of attention. Then, it concatenates all the attention heads and multiplies them with a new weight matrix W^O. As Equation (3-7) shows, it has 8 different weighted matrices (QW_i^Q, KW_i^K, VW_i^V), which are randomly initialized. This provides the attention layer to have different representation subspaces at different positions, and the model can learn richer and better representation for every word. After computation of attention, outputs of the multi-head attention are fed to a feed-forward neural network which has a single layer with 512 hidden units' perceptron and then it becomes the output of the encoder layer. Figure 3-5 shows the steps how the output of the encoder is calculated and the Single Attention Layer explains the process of single head calculating the attention from input sentences.

$$MultiHead(Q,K,V) = Concat(head_1, \dots, head_h)W^O \tag{3-7}$$

$$\textbf{where } head_i = A(QW_i^Q, KW_i^K, VW_i^V)$$

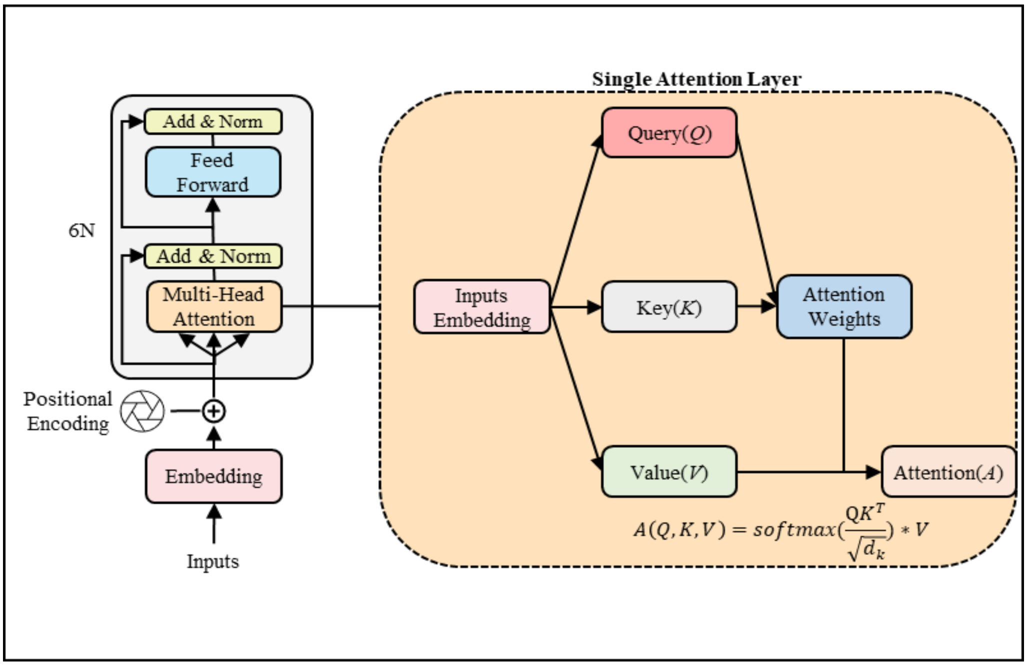

Figure 3-5 Encoder Architreture of Transformer

(2) Bidirectional Encoder Representation (BERT) for Sentence Embeddings: BERT is the baseline word embedding model of BERTopic and is a pre-trained Transformer Encoder stack. BERT consists of two processes: *pre-training* and *fine-tuning*. The special classification token called CLS is assigned for the first position of every sequence to the input of the model. CLS is the comprehensive token containing information on sequence representation for classification tasks and is used for the final hidden stage. In the pre-training process, BERT is pre-trained using unlabeled data, such as books and Wikipedia for the purpose of fitting to different tasks. Especially, the authors masked some of the tokens for training a deep bidirectional representation, 15% is suggested as an optimal percentage by authors and made the model to predict masked words. The outputs from stacked encoder layers and the final hidden layer are fed into softmax to train the whole model. In the fine-tuning stage, BERT first is initialized with pre-train parameters and update parameters with the labeled data, text corpus of Stanford Natural Language Inference (SNLI) and Multi-Genre Natural Language Inference (NLI) are used for SBERT.

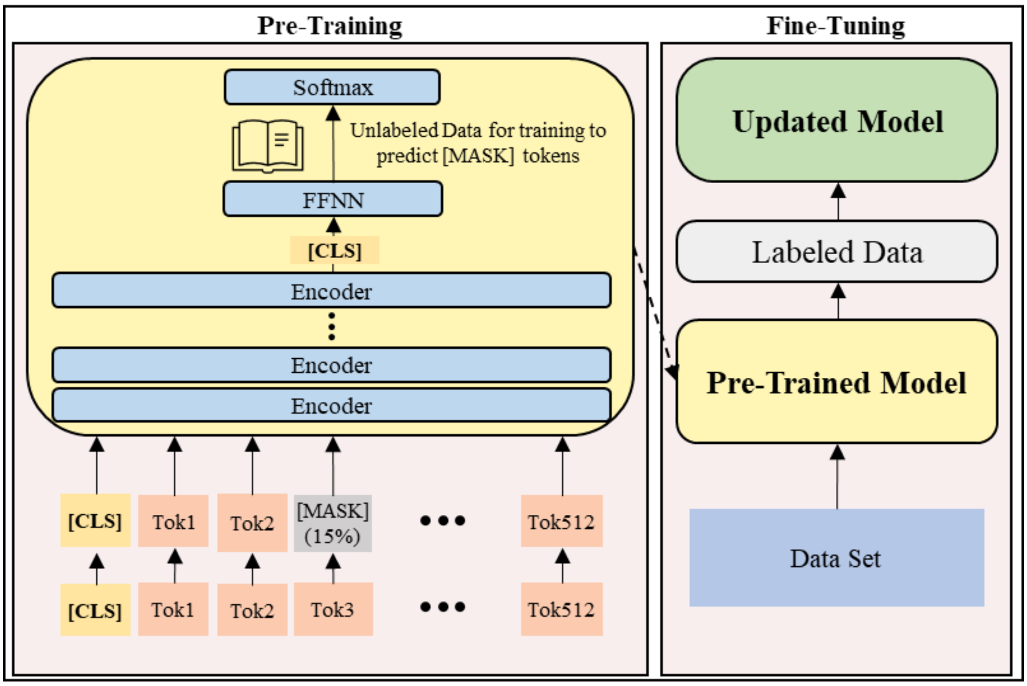

Figure 3-6 Pre-training Process of BERT

(3) Document Embeddings: In BERTopic, it assumes that documents including the same topics have similar semantics. The original BERTopic model mainly utilizes the SBERT to perform document embeddings. SBERT is a modified model of BERT to overcome some problems in dealing with sentences. In general, clustering and semantic search of sentences map semantically close sentences to the vector space. When using BERT to conduct sentence-pair regression tasks to find the similarities of sentences, two sentences are passed to the transformer network. For example, when we have 10,000 sentences, the pair including the highest similarity requires BERT to calculate a 49,995,000 (n*(n-1)/2) combination of sentences and takes excessive time. To avoid this problem, the author of SBERT modified the BERT by adding some functions, Siamese and triplet networks. Figure 3-7 shows how it is different from the original BERT fine-tuning process. In the default setting of the SBERT, it takes the means of the BERT output to get the fixed-sized sentence embedding by appending the pooling layer. Siamese network in the fine-tuning process makes the model for having two identical BERTs in parallel and they are sharing same network weights to two different sentences. After that, concatenate the two Siamese BERT outputs u, v and |u - v| which determines the difference between the two vectors. With this vector, finally, feed it into the Softmax classifier and update the parameters to minimize the cross-entropy loss. SBERT has trained with the SNLI and Multi-Genre NLI datasets. SNLI data is a set of 570k human-written English sentence pairs with 3 labels: entailment, contradiction, and neutral. Multi-Genre (NLI) has 433k sentence pairs labeled entailment information that covers a range of genres of spoken and written texts.

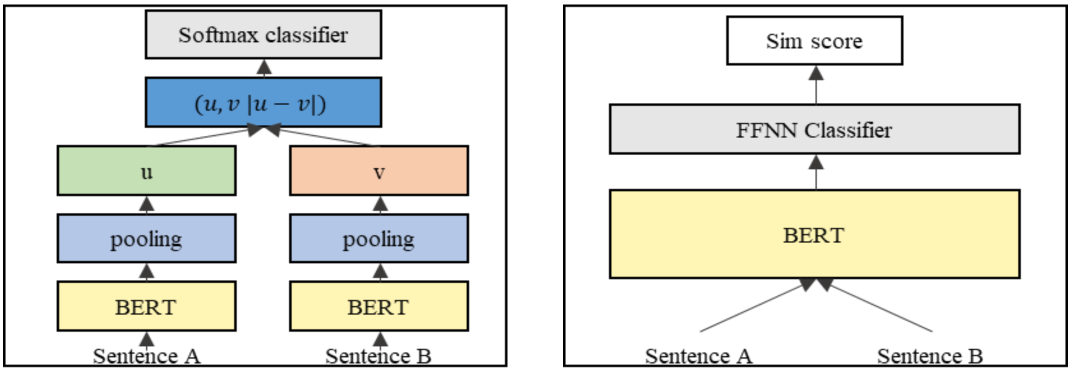

Figure 3-7 Fine-tuning Architecture(left) and Calculation of Sentence Similarity(right) of SBERT

(4) Dimension Reduction and Document Clustering: After building the sentence embedding, BERTopic does the clustering process of the embeddings for getting insightful clusters which are the topic of sentences by utilizing a clustering method called Hierarchical Density-Based Spatial Clustering of Applications with Noise(HDBSCAN). However, since the sentence embeddings with the MINILM model have 384 dimensions, the computational cost is high, so clustering efficiency is low. To optimize the clustering step, BERTopic includes an embedding compress step called the dimensionality reduction step through Uniform Manifold Approximation and Production (UMAP) algorithm. UMAP algorithm reduces the dimension of vectors by determining the likelihood that data points can be connected with the number of neighbors that the user set up. Based on the distance between data points to their neighbor, UMAP chooses the circular boundary for each neighbor. UMAP can effectively ensure the local structure and preserve the original construction of the data at the same time.

(5) Topic Representation: With the clustered documents, BERTopic assigns each cluster to the topic that can represent the topic. The modified TF-IDF is mainly used to calculate the importance of the documents for each topic and it is called c-TF-IDF by the author of BERTopic.

$$\textbf{c}\text{-TF-IDF} = \frac{f_{t,c}}{\sum_{t' \in c} f_{t',c}} * \log(1 + \frac{A}{tf_t}) \tag{3-8}$$

It first calculates the frequency of the term t in class c. Class c here represents the collection of every document in each cluster calculated in the prior step and combined into one document. Then, multiply the logarithm of the inversed class frequency that includes the information on how terms are important in the class. Inverse class frequency is calculated by dividing the average number of words per class c by the frequency of the term t through whole classes. Through iterating this process, BERTopic derives the topic-word distributions for each cluster and reduces the number of topics by merging with a similar cluster.

3.2.6 Text Regression

Comments data not only have unstructured data but also have structured data, such as the likes of the comments, and the sentiment index of comments that can be extracted by employing the NLP techniques. Specifically, when numerical data is combined with textual data, it enhances the effectiveness of the research (Jia, 2020). Moreover, when it is investigated with the topic modeling method that makes it possible to categorize comments, it provides systematic and insightful information to understand consumers deeply (Lucini et al., 2020).

In this thesis, the number of thumbs up on comments is utilized as one of the main factors to be analyzed for the deep understanding of the consumers. Thumbs up in comments are a way for users to show their appreciation or agreement with a comment. It also allows other users to see which comments are popular or helpful. In a study by Zhao (2021), thumbs up were found to be used as an indicator of consumer sentiment or satisfaction (Zhao, 2021). In addition, sentiment indices of the reviews are counted as important indicators to understand how consumers react to the products or services, and also for YouTube to understand the consumer response to the content of the videos (Jelodar et al., 2021). Accordingly, analyzing sentiment indices alongside the number of thumbs up allows for an in-depth understanding of the experiential value of telepresence by considering both emotional responses and audience satisfaction. The technique of counting the number of thumbs up and sentiment index on YouTube comments employing a regression model contributes to the scientific foundation of the thesis by offering a quantitative measure of consumer sentiment, incorporating social validation, and enabling hypothesis testing.

The first is to detect if there is a significant relationship between the sentiment indices of the comments and the number of thumbs up of comments. The result of this analysis provides insights into how the sentiment expressed in comments influences the audience's reaction and engagement, as measured by the number of thumbs up. It is expected to give a new angle of consumers' response that was not found in the condition that "writing" action has to be happened by viewers. Since the range of the number of thumbs up on comments is from 0 to 70,000, I took the natural logarithm of this value. In addition, I used the Valence Aware Dictionary and Entiment Reasoner (VADER) model which works accurately, especially for the comment data from social media (Vashishtha et al., 2019) to get the sentiment index of each comment. In this thesis, Positive Sentiment Index (PSI) and Negative Sentiment Index (NSI) are used for the additional numerical values. The value of the sentiment index is from 0 to 1 so the higher the value, the stronger sentiment of positive and negative that comment has.

Hypothesis 1. *H1*: The number of thumbs up has a significant relationship with the positive (and negative) sentiment index of comments. The equation is

$$\log\,(likes_i) = \beta_0 + \beta_1 psi_i + \beta_2 nsi_i + \epsilon_i \tag{3-9}$$

where $\log\,(likes_i)$is the logarithm number of thumbs up for comment *i* which takes a natural log; psi_i and nsi_i is the sentiment index of each comment respectively; ϵ_i is the disturbance term.

One main purpose of this paper is deeper research in various angles into the public opinion of VR concert videos using comment data. Hypotheses 2, 3, and 4 analyze the theme of comments derived through topic modeling along with numerical data. For this analysis, comment categories from topic modeling were set as the independent variables to identify how words in each theme impact sentiment indices and thumbs-up counts which are used for the dependent variables. First, I calculated the probability of comments assigned to each topic using frequency of vectorized terms with the topic distribution probability. Then summed all topics' probabilities into each categorized theme to obtain the probability of which theme the comments is assigned to. This method provides more systematic use of comment data in the purpose of regression analysis compared to the previous hard categorization for deciding the exact topics. Finally, the ordinary least squares (OLS) regression analysis is performed to identify which theme had the most significant impact on sentiment index and thumbs up count for each comment.

Hypothesis 2 is to find out how the sentiments of comments from VR concerts viewers are related to categorized comments. By categorizing comments based on the identified themes through topic modeling, it is possible to quantify the influence of each theme on the sentiment expressed in the comments. This hypothesis identifies the thematic factors that contribute to positive or negative sentiment among the audience, contributing to a deeper understanding of public opinion regarding VR concerts. This hypothesis provides the clue which aspects of VR concert affected usage of emotional word in the comment.

Hypothesis 2. *H2*: Themes of the comments significantly affect the PSI (and NSI) of the comment. The equations of the hypothesis 2 is

$$psi_i = \gamma_0 + \sum_{t=1}^{n} \gamma_t theme_i^t + \epsilon_i \tag{3-10}$$

$$nsi_i = \gamma'_0 + \sum_{t=1}^{n} \gamma'_t theme_i^t + \epsilon_i \tag{3-11}$$

where psi_i and nsi_i are the index of positive and negative sentiment score of comment i, γ_0 is the intercept of the comment that is not assigned to any other topics, n is the number of theme extracted from topic modeling, $theme_i^t$ is the probability that comment i is categorized to the theme t, and the ϵ_i is the error terms.

Hypothesis 3 aims to investigate the factors that contribute to viewers' empathy in VR concerts. Specifically, the relationship between the number of thumbs up in each comment and the theme of the VR concert comment is analyzed. By analyzing the impact of different themes on the engagement level indicated by thumbs up, this research identifies which themes tend to generate higher levels of audience engagement and appreciation. This analysis provides visions into the aspects of VR concerts that appeal to the audience, enabling them to specify themes that have a significant influence on the number of thumbs up received.

Hypothesis 3. *H3*: Themes of the comments significantly affect the number of thumbs up on comments.

$$\log(likes_i) = \delta_0 + \sum_{t=1}^{n} \delta_t theme_i^t + \epsilon_i \tag{3-12}$$

The equation of hypothesis 3 is similar to hypothesis 2 but the dependent variable is changed from the sentiment index to the natural log of the number of thumbs up.

Finally, hypothesis 4 verifies whether the usage of terms in themes of the VR concert changes over time. Specifically, it sets the dependent variable as the period before and after the Covid-19 pandemic to find out more about the use of terms and themes that differ by the period. Therefore, the larger the coefficient value, the more specific theme was written after the Covid-19 pandemic (2022~), and the smaller it tends to be written before the Covid-19 pandemic (~2021). This can clearly show consumer perception of VR concerts after the pandemic by recognizing which aspect of VR concerts prevailed at the end of the Covid-19 pandemic.

Hypothesis 4. *H4*: Themes of the comments are different in dissimilar periods.

$$Period = \varepsilon_0 + \sum_{t=1}^{n} \varepsilon_t theme_i^t + \epsilon_i \quad (3\text{-}13)$$

The equation of hypothesis 4 is similar but the dependent variable of hypothesis 4 is binary variable, where if *Period* is 0, it means that comment is posted before and during the Covid-19 pandemic and if *Period* is 1, comment is written after the Covid-19 pandemic which is after 2022.

The four hypotheses presented within this thesis assist in clarifying the relationship between comment themes, sentiment, engagement levels, and temporal shifts, which offers factual evidence as well as quantitative measurements to comprehend the telepresence's experiential worth. Especially, it reveals various aspects of VR concerts that enhance the immersive and appealing attributes of VR content. Therefore, this approach advances awareness of how the general public experiences and interacts with VR events and states the development of a scientific basis for evaluating the experiential value of telepresence in the context of VR leisure.

3.2.7 Dynamic Topic Modeling

Early topic modeling techniques could not keep up with the alternation of topics in different contexts, such as different timelines and metadata since they preferentially generate topics with relevant words and so it is static. However, c-TF-IDF makes it possible to indicate how topics evolve sequentially and which topic representations reflect them. In the context of a different timeline, they assume that the global topic and the temporal nature of topics are independent.

$$W_{t,c,i} = \frac{f_{t,c,i}}{\sum_{t\prime \in c} f_{t',c}} * \log(1 + \frac{A}{tf_t}) \quad (3\text{-}14)$$

$$Global\ Tuning = \frac{W_{t,c} + W_{t,c,i}}{2} \quad (3\text{-}15)$$

$$Evonlutionary\ Tuning = \frac{W_{t,c,i-1} + W_{t,c,i}}{2} \quad (3\text{-}16)$$

So, it first organizes the global topic irrespective of their temporal nature of them. Then, it can develop the local representation of each topic by multiplying the term frequency of documents at each timeline *i* with the global IDF values calculated to organize the global topic. Final, two methods were suggested to fine-tune the topic representation of specific timelines *i* called global tuning and evolutionary tuning. By averaging the topic representation of timeline *i* with the matched global representation, globally induces each representation to become more similar to the global representation. The evolutionary method is work by averaging the representation of the timeline *t* with the representation at timeline *i-1*, so it allows us to show how the topic developed over time.

Dynamic topic modeling can also be used to investigate how topics are different by types of videos and can be done without the fine-tuning process.

$$W_{t,c,i_{pre}} = \frac{f_{t,c,i_{pre}}}{\sum_{t\prime \in c} f_{t',c}} * \log(1 + \frac{A}{tf_t}) \quad (3\text{-}17)$$

$$W_{t,c,i_{vr}} = \frac{f_{t,c,i_{vr}}}{\sum_{t\prime \in c} f_{t',c}} * \log(1 + \frac{A}{tf_t}) \quad (3\text{-}18)$$

$$W_{t,c,i_{after}} = \frac{f_{t,c,i_{after}}}{\sum_{t' \in c} f_{t',c}} * \log(1 + \frac{A}{tf_t}) \tag{3-19}$$

Where the term frequency of different types of concert videos, comments from general concert videos of the pre-Covid-19 pandemic i_{pre}, VR concert videos i_{vr}, and after Covid-19 pandemic i_{after} in this thesis.

4 Result and Discussion

The result of this study is mainly obtained by analyzing the comments data gathered from YouTube. In detail, the first section is about the specific explanation of data, for example, where it is from, how it is collected, and the way it is prepared for getting an accurate result of the analysis. After, for the purpose of getting a broad understanding of the data, I investigated the details of the data and conducted a descriptive analysis of the data. This part included the specific information of the content of data investigated in various ways, feature extraction using TF-IDF word embedding model. Finally, with an understanding of the data, I utilized the BERTopic and text regression to research consumer thinking toward VR concerts and research how consumer thinking is different when they enjoy live performances through general recorded videos.

4.1 Problem Description

Currently, despite widespread illegal downloading of recorded music files and people, don't willing to pay for music, the popularity of live music performances is still increasing. Key expectations consumers want to enjoy live music performances are *Experience, Engagement, Novelty,* and *Practical* (Brown et al., 2017b). However, with the arrival of the Covid-19 pandemic and social distancing, people couldn't enjoy the live music performance for around 2 years to prevent the contagion. At this time, content with VR technologies was a critical method to hold live music performances remotely, and it proliferated in many ways. After the omicron variant, some of the western countries started to lift the social distancing policy, and after 2022 Asian countries, such as Thailand, South Korea, and Japan began to ease the Covid-19-related policies as well (Hale et al., 2021b). With the trend of retaliatory consumption after two years of restrictions, the sales of live music performances are soaring higher than ever (Live Nation Entertainment, 2022b). Under the context of this industry situation, it is important to understand the consumers' opinion toward a new form of live performance that became popular under the restrictions of the Covid-19 pandemic and if they are willing to keep enjoying it to estimate the value of metaverse leisure and its expandability. Since this new type of live performance was held online, there is a characteristic that unstructured data is more generated than in traditional on-site live concerts, and it is necessary to apply a new methodology to meet this change. Therefore, in this research, Word Embedding and Topic Modeling are used to follow and predict changes in the live music industry.

4.2 Data

In this study, YouTube comments data is utilized as the main data to investigate the public opinion of VR concerts. Especially, comments from the most successful virtual concerts held via the platform Fortnite were used for the main data. The reason I selected the comments on these videos is their popularity and representation. Although some virtual concerts were held during the pandemic period through some other platforms, no video has more comments and views than the Fortnite platform. Furthermore, people are still enjoying the video and comments are being updated, which means that public opinion can be compared between the peak of the pandemic and the period when social regulations are gradually decreasing. In addition to this, all singers from VR concerts are the most popular singers in the world, so they have multifarious concert videos not only for the VR concert, and I can keep the consistency of the dataset for additional research with their general concert videos. Finally, the data is from VR concerts that are fully made in virtual condition, not only for the singer but for the audiences, stage, special effects, etc. are made up of graphical figures. So, it is more informative to understand the metaverse leisure since there are some other types of XR/VR concerts, for example, audiences can only take part in the concert through the chat box or just make the virtual stage with the real singers. For the comparable comments data conducting additional research, I exploited all the officially uploaded concert videos comments of Travis Scott, Ariana Grande, Marshmello, and Juice Wrld from the June of 2021 as the "after Covid-19 period", when the first offline live performance of Ariana Grande was held during the phasing out stage of the Covid-19 pandemic and from 2018 to 2019 for the "pre Covid-19 period". In short, in this research, the three separate periods of data, are from 2018 to 2019 for pre Covid-19 pandemic period, from 2020 to 2021 for the peak of the Covid-19 pandemic, and from the mid of 2021 to 2022 for the after-Covid-19 pandemic period and the detail information of each video is attached in Appendix-A.

4.2.1 Data Collection

Main data is collected from the VR concert videos held via Fortnite. In detail, comments from "Marshmello Fortnite Concert Live at Pleasant Park (2019)", "Travis Scott and Fortnite Present: Astronomical (2020)", "Rift Tour Featuring Ariana Grande (2021)", and "Fortnite Juice Wrld Concert (2022)" are used as the main data. The number of comments is 10,298 gathered in 2022-12-20, and the total number of views is 274,190,475 from 5 videos. In terms of after the Covid-19 pandemic period, I gathered 13,905 comments from the 21 videos and the total number of views is 318,714,531. For the pre-Covid-19 pandemic period, the number of comments gathered from 16 pre-pandemic period videos is 12,351 and viewed 115,910,529 times. This 2 years' period for both pre- and after- Covid-19 pandemic has the same period of strict control over the mass gathering. Overall, 37,827 comments from 42 YouTube videos viewed 708,815,536 times around the world are used to achieve the purpose of this thesis. Table 4-1 shows the summary information of the dataset. To get the huge comment dataset, I used the selenium library of Python.

Table 4-1 Summary of the dataset

Type	**Uploaded Year(range)**	**Videos(n)**	**Total Views**	**Number of Comments**
VR Concert	2019-02-02 ~ 2022-09-10	5	274,190,475	10,298
General (pre-Covid 19)	2018-03-24 ~ 2019-10-12	16	115,910,529	12,351
General (after-Covid 19)	2021-06-01 ~ 2022-10-08	21	318,714,532	13,905

Table 4-1 (continued)

Type	Uploaded Year(range)	Videos(n)	Total Views	Number of Comments
Overall	2018-03-24 ~ 2022-10-08	42	708,815,536	37,827

4.2.2 Data Preprocessing

After scrapping all the comments data, I preprocess it to ensure the quality of the data. Especially, for short-text data from social media, like YouTube and Twitter, it is needed specific steps for cleaning the data since those kinds of comments are written in informal ways that depend on the comment writers (Naseem et al., 2021). So, I added some more steps for the data preprocessing, not only classical preprocessing steps but for those proposed by Naseem et al. (2021). Figure 4-1 shows the whole steps of the data preprocessing and below are the specific explanations of each step.

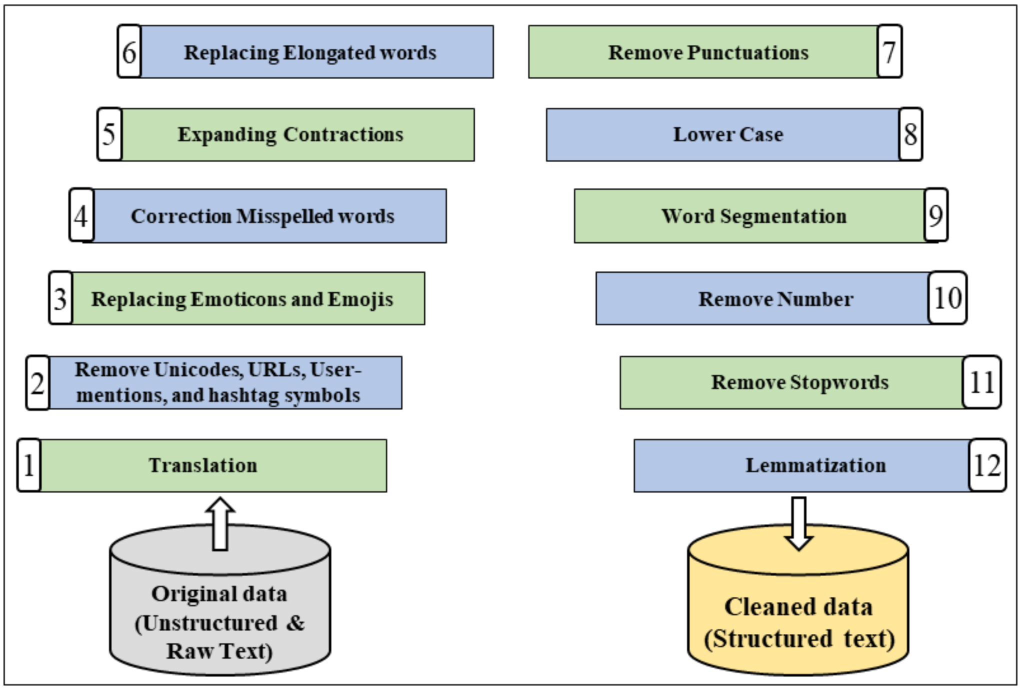

Figure 4-1 Data Preprocessing Steps for Short Text

(1) Translation - YouTube is one of the most popular video platforms in the world which is available in over 91 countries and supports 80 different languages. Consequently, comments data have noise because of different languages and needed to be unified for better analytic results. In this thesis, I translated all the non-English data to English data using google translator API. 86.7% of the comments are written in English and remained 13.3% of comments are written in a non-English language. The example from actual data is below:

Before**:**

Eu tava no evento, foi o evento MAIS FODA do fortnite, lembro que estava com meus amigos vendo esse concerto incrível, precisamos de mais.

After**:**

I was at the event, it was the COOLEST fortnite event, I remember I was with my friends watching this amazing concert, we need more...

(2) Remove Unicodes, URLs, User-mentions, and hashtag symbols **-** Some Youtube comments included URL user-mentions (@) and hashtag symbols (#) to write supplemental information, for example, recommending other videos, emphasizing the favorite part, etc. That information is readable for humans, but it is considered as noise in order to text analysis. In this research, the text is removed and hashtag and user-mentions text is modified to normal text. The example from actual data is below:

Before:

@Marshmello do you miss plesentpark? And you could redo a concert with fortnite?

After:

Marshmello do you miss plesentpark? And you could redo a concert with fortnite?

(3) Replacing Emoticons and Emojis **-** Emoticons and Emojis (eg, ":)", ":|") give the information of the feelings, a nuance of comment, so it is an important source of data. In this research, I used a python library called *emot* to replace them with valuable text data. The example from actual data is below:

Before**:**

I've listen to this many to many time :)

After:

I've listen to this many to many time Happy_or_smiley

(4) Correction Misspelled words **-** Incorrect spelling usually happens in comments data. In addition to this, some writers intentionally use misspelled words by abbreviating them or by using slang. When considering that those kinds of words are used in a specific context or among a particular group, it needs to be corrected to clear words. I used the *contextualSpellCheck* library based on the BERT model in this thesis to correct incorrect spelling. The example from actual data is below:

Before:

i haven't seen this in 2 yrs and dam bruh i forgot how hype this event was easily one of the best event in the games history

After:

i haven't seen this in 2 years and dame i forgot how much this event was easily one of the best event in the games history.

(5) Expanding Contractions **-** Expanding contractions allow efficient lemmatization in the later step. For example, when the word is written "*can't"*, it will be lemmatized to "*can"* and "t". Through this step, words will be changed to "*can not*" and lessen the text data's noise.

(6) Replacing Elongated words - When people write comments, they sometimes write them in a longer way than their original words to express their sentiments. For example, there are some words "yeeees", "yeeeeee", "woooow" in the dataset, and could be changed to "yes", "ye", and "wow". It is suggested when the same characters are consecutively written more than three times, they can be considered elongated words and replaced with one character (Kiritchenko et al., 2014).

(7) Remove Punctuations - Removing punctuation is one of the classical pre-processing steps that eliminates line change for the comment data. For humans, line change makes it simpler to read, but for the machine, it is just a white space that doesn't have any meaning.

(8) Lower Case - This step is conducted to unify the form of words. When machine understands text data, they don't have specific grammar, so *Apple* on the first of the sentence, and *apple* is considered a different word. To avoid this misleading, make all the words lowercase through this step.

(9) Word Segmentation - Users sometimes write comments with hashtags and in informal ways, especially concatenating all the words without spacing. It is because to keep the whole sentence belonging to the hashtag or sometimes to avoid length limitation. In this thesis, I remove the hashtag from the prior step and then segment the sentence by word utilizing *wordsegment*. The example from actual data is below:

Before:

#Arianagrande #Godisawoman

After:

ariana grande god is a woman

(10) Remove Number - Numbers in comments are usually deleted when conducting text classification. Especially numbers from YouTube comments to point out the most favorite part of the Video, so it doesn't include any information. However, in this thesis, investigating people's thinking over time is essential, so year information would be an important cue for understanding it. Therefore, numbers without expressing the year would be removed from this thesis.

(11) Remove Stopwords - Remove the meaningless words with the stop words from the Natural Language Toolkit (NLTK) python library (eg, "the", "a", "an"). In addition, investigate the term frequency graph to find some odd words, which are still miss-spelled, and unintentional conversions during pre-process step to remove additional stop words. As a result, some of the proper nouns conversed from the name of the singer such as "Travis" and "Scott" to is added to the manual stop words and can catch more informative words. However, since BERtopic is the transformer model that considers the context of the sentence, it is suggested to keep the original shape as possible of the data. Therefore, for the topic modeling, I conducted preprocess without removing manually added stop words.

(12) Lemmatization - Applied NLTK lemmatize to group different forms of words in order to analyze them as a single-word linguistic (eg, "rocks" to "rock" or "better" to "good").

4.3 Descriptive Results of the Data

In this section, I meticulously examined the data to completely understand it before conducting the topic modeling. First, I investigated the feature of the dataset. In-depth, the distribution of the number of comments data per singer, time, and type of videos is studied to understand the characteristic of the dataset. Moreover, the most popular comments which have the highest number of "likes" among data from VR concerts are investigated. I could find which kinds of comments are most upvoted by other viewers and the themes that they want to share. Second, TF-IDF word embedding model was implemented to find which terms take an important role in the VR concert comment data. This helps me choose the optimal topic modeling strategy by identifying influential terms in the comment data. In addition to this, a comparison of the TF-IDF score of comments to general concert videos was conducted to robustly research how the distribution of words is different in each class. The result of this step inspires what kind of topic differences there would be between classes.

4.3.1 Descriptive statistics of Comments by Components

The main data of this research is obtained from 5 VR concert videos and additional data from 37 general concert videos. In this research, the data is divided by period and concert type for comparative research, moreover, in this section, it is split by singers and investigates the statistical description of each separation. Table 4-2 shows the descriptive statistic of the comments of each separation. The component column represents the criteria by which the data are divided, the contents column is the elements made up of each component, the range is the minimum and maximum number, and the STD is the standard deviation representing the divergency of the data for each content. First of all, the data set divided by year has a large STD for each content, thus the difference in the quantity of data by year is the largest among other components. Data divided by singers also have a relatively high STD, and the number of max contents exceeds 5,000, which means that half of the data has been collected from one singer. The class component refers to the type of each concert and the criteria for dividing the general video by year, which does not show much difference in the amount of data by class, therefore it is balanced data.

Table 4-2 Descriptive Statistic of the Comments of Each Separation

Components	Contents	Range	STD
Year	2019, 2020, 2021, 2022	241 ~ 6000	2474.73
Singers	Marshmello, Travis Scott, Ariana Grande, Jucie Wrld	1313 ~ 5097	1773.09
Class	VR concert, General Concert Video(Pre-Covid19), General Concert Video(After-Covid19)	10298 ~ 13905	1992.6

Figure 4-2 shows more detail of the data distribution by each content. From the year distribution (a), it can be found that more comments were written over time, especially half of them written in 2022. When examining data distribution by singer (b), Ariana Grande’s video collected the most data, followed by Travis Scott, and the other two singers appear similar. Finally, in the data distribution by class (c), the main data, VR concert, have the fewest comments but does not show a significant difference with other classes.

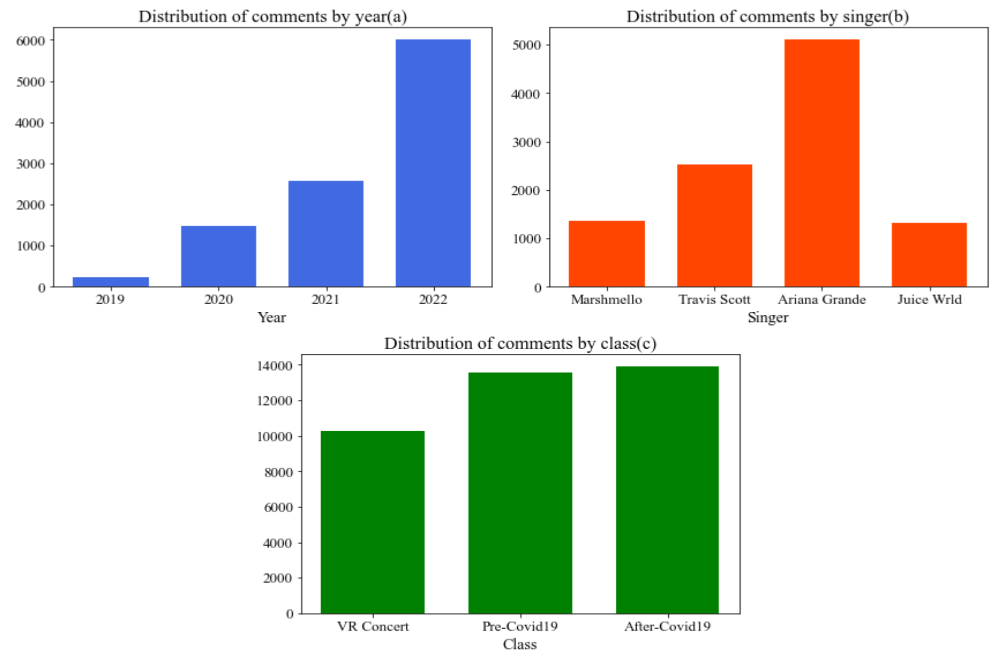

Figure 4-2 Distribution of the Data by Each Component

In addition to this, I selected 20 comments with the highest number of likes to investigate which comments were most sympathized with among viewers. Table 4-3 shows the rank, comments, published year, number of likes, and values that writers want to share. Specifically, values are derived from prior research that concert crowds expect for the live concert (*immersive, artists, visual stimulation, social interaction*), however since one of the biggest motivations to write comments is social interaction (Springer et al., 2015), most comments are written to interact with other people, so this value is to be specified with another values in this research. There is a value called *undefined* in this table and they will be defined with the theme of comment clusters extracted by the BERTopic. Specifically, in this section, *immersive* is determined with the comments that viewers feel an immersive feeling in a virtual concert, *artist* is an expression of love toward a singer as their fan, and *visual stimulation* is literally about the visual stimulation, such as stage, avatars of the videos. In Table 4-3, *visual stimulation* is the most popular value that comments readers prefer, the *proximity of the artist*, and *being there* are the following as the most popular comments.

Table 4-3 Popular comments from main data

Rank	Comment	Year	Likes	Theme
1	I'm not a Fortnite player, but I appreciate how epic games satisfies their player	2020	52,000	undefined
2	"Yeah I've been to a Travis Scott concert".	2020	33,000	immersive
3	Fortnite: "what effects do you want" Travis: "you ever tried acid?".	2020	33,000	visual
4	Who's watching this after hearing about the Travis Scott event?	2020	30,000	undefined
5	The effects artist was probably the highest in the room.	2020	28,000	visual

Table 4-3 (continued)

Rank	Comment	Year	Likes	Theme
6	I’m not a Fortnite fan but this. This was beautiful.	2020	26,000	undefined
7	What was your favorite moment?	2019	26,000	undefined
8	If you ever feel useless, just remember there was a stage in this concert...	2020	22,000	undefined
9	Imagine playing a normal game of Fortnite and some random giant shirtless man appears out of nowhere and starts rapping	2020	20,000	visual
10	Fortnite: Builds Stage Travis Scott: Uses Whole Map	2020	20,000	visual
11	Marshmello’s was a concert. Travis Scott’s was an experience.	2020	18,000	immersive
12	Even if you hate fortnite, you can't deny that event was incredible	2020	16,000	undefined
13	A magical ride from start to finish	2021	16,000	visual
14	What a freaking event!	2019	14,000	undefined
15	9 year olds seeing travis irl: He’s much smaller in person	2020	12,000	undefined
16	ty for letting me fly with u ari	2021	10,000	artist
17	ariana going up the stairs to heaven while “The Way” ft. Mac Miller was playing, one of my favorite tributes ever <3	2021	8,100	artist
18	Its funny how many kids became travis scott fans because of this event	2020	7,600	undefined
19	Imagine playing a normal game of Fortnite and some random, giant shirtless man appears and starts rapping out of the blue.	2020	7,200	visual
20	Ariana's moving forward so fast.. She’s already touring other universes. So amazing.	2021	6,600	artist

4.3.2 Lexical Analysis with TF-IDF

TF-IDF score represents how specific terms are important in the main data. In this thesis, I used a uni-gram TF-IDF word embedding model that considers just one word to calculate the TF-IDF score to understand the keywords from the main data. In Table 4-4, there are 15 terms taking a crucial role in the comments from the VR concert video. Also, there is information on how specific words frequently appear from the main data and the rank of frequency is in the parenthesis. The result table first shows that the terms *event* and *concert* have high term frequency and TF-IDF score which is ranked first and third in the corpus. It reveals that the dominant comments writers not only consider VR concerts as actual concerts but also those terms are important to account for the opinion of viewers enjoying VR concerts. However, the term *game* also has a high TF-IDF score, and it can be explained that the platform of the VR concert is important in the response of the viewers.

Second, prevailing terms present a positive sentiment that implies the comments are usually written in a positive mood. In detail, 4 out of 15 terms, *best*, *love*, *like*, *good*, have the high TF-IDF score in the table. Furthermore, the term *ever* could be considered a positive term since they are normally used with praising words like best. Third, there are some noticeable words *year*, *one*, *time*, *miss*, and *world* that people miss for a specific period in the table. Given the period that most comments are written after the Covid-19 pandemic, it can be interpreted in two ways. First, it can be interpreted that its viewers are missing the world before the Covid-19 pandemic when there were no restrictions for mass gatherings and live performances. On the other hand, since the majority of remote and VR concerts were held during the peak of the Covid-19 pandemic, it also can be supposed that viewers long for the period when they can enjoy the live concert remotely or in special ways. This question will be clarified with a dynamic topic modeling method that takes the metadata, and the published year of comments, as a factor in explicating the trend of public opinion.

Table 4-4 TF-IDF Score Table from Main Data

Rank	Term	Term Frequency(rank)	TF-IDF Score
1	event	1979 (1)	476.724533
2	best	972 (3)	354.529468
3	concert	1187 (2)	321.803416
4	love	780 (5)	305.934645
5	like	856 (4)	210.532912
6	good	571 (9)	202.109427
7	year	489 (12)	162.534553
8	game	582 (7)	156.362078
9	ever	406 (17)	150.263589
10	get	588 (6)	149.091864
11	make	579 (8)	148.217259
12	one	537 (10)	147.563933
13	time	511 (11)	147.036708
14	miss	352 (23)	146.36717
15	world	413 (16)	145.818749

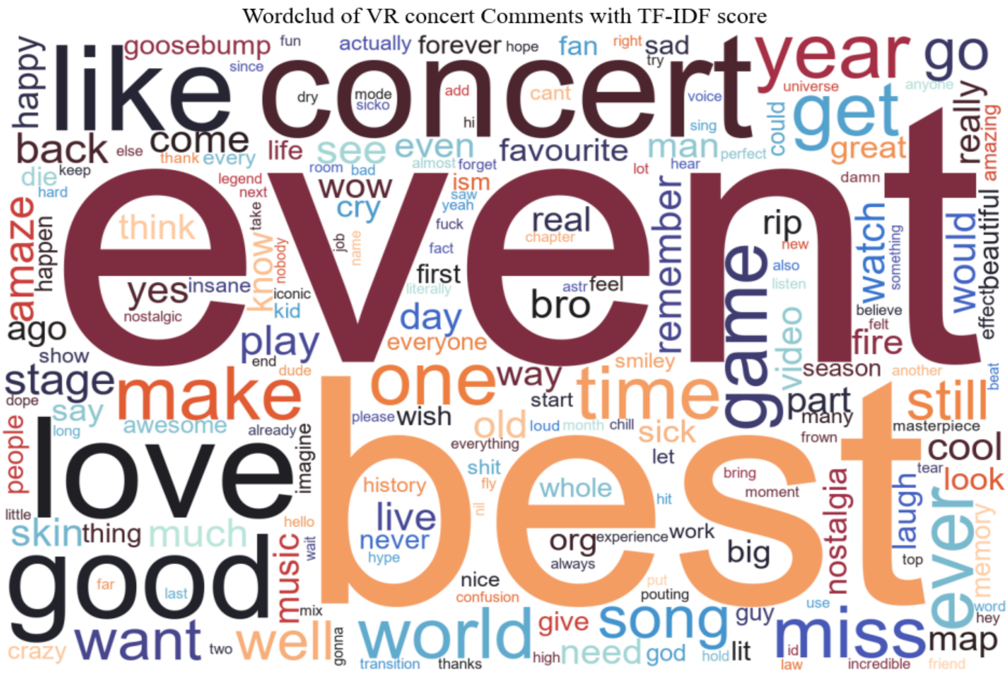

Figure 4-3 TF-IDF Word Cloud from Main Data

Along with Table 4-4, Figure 4-3 displays more terms with high TF-IDF scores differed by the size of the font. In parallel to terms from the table, positive terms are dominant with high TF-IDF scores in the word cloud, such as *favourite*, *great*, and *goosebump*. Meanwhile, I can find some significant words that were not presented in the table but were far from the dominant words, *rip* and *die*. Rip is the abbreviation of “Rest In Peace” normally used to honor the dead. According to the limited information with only terms and TF-IDF score, it is unclear what these words are exactly about, but the fact that it is shown in the word cloud gives the clue that it is needed to focus on these terms in the following result with the topic modeling method.

In summary, through observing the TF-IDF score of terms, I can confirm that the positive sentiment is prevailing in comment data from VR concert videos. Nevertheless, there is some less understood context because of the limited information, first is the longing period related to the terms like *miss*, *nostalgic*. This will be identified with the dynamic topic modeling method in the next Section 4.4.2. Second, it displays several exclusive terms, such as *rip*, *die* that are uncommon compared to other often displayed terms in the comments but are nonetheless regarded as crucial to comprehending the comments data. Section 4.4.1 will clarify these terms according to the type of topic they pertain to.

4.3.3 Comparison of TF-IDF Score with General Videos

In this section, besides the lexical analysis of main data using the TF-IDF method, I compare the prevailing terms with high TF-IDF scores from the comments of general concert videos. Figure 4-4 demonstrate 20 terms with high TF-IDF scores from embedded comments of VR concert videos and general concert videos, respectively. From both figures, one of the prominent similarities is that terms representing positive sentiment are dominant, such as *love*, *best*, *like*. This similarity proves that comments are written in positive ways and people are satisfied to enjoy both types of concert videos.

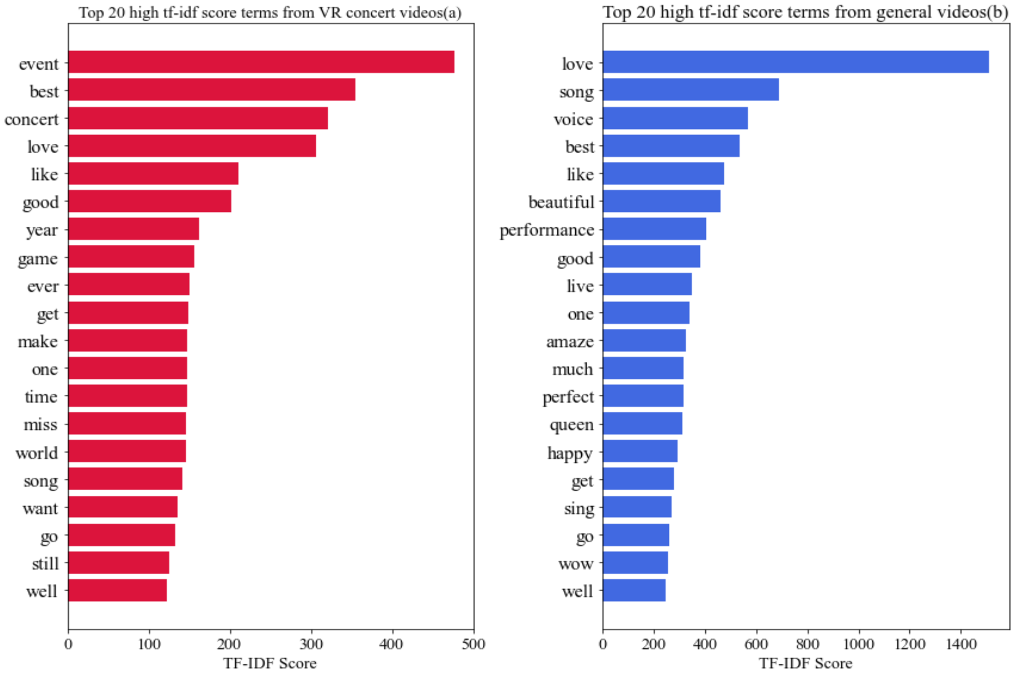

Figure 4-4 20 TF-IDF Score Comparison Between Comments from VR concert videos and General concert videos

Terms dissimilarities between two figures indicate more interesting information. First, terms explaining two different concert videos are slightly different, for example, *event* and *concert* are crucial terms from VR concert videos, meanwhile, *song*, *voice,* and *performance* are the important term representing the comments of general videos. Those terms from both figures are used when expressing the live music show, however, it is obvious that the emphasis of the concert is different. Specifically, from the terms *event*, *concert* of VR concert videos, it can be speculated that VR concert videos have a broaden meaning of content beyond the recorded live performance videos. Terms *song*, *voice*, and *performance* from general concert videos are supporting this speculation with the tendency that people are more attentive to the component of the recorded performance, rather than consider it as the event or concert. This discrepancy suggests that people perceive videos as two different types of content depending on the two kinds of recorded concerts they have seen.

Second, terms relevant to the longing emotion, such as *miss*, *time*, and *still* exclusively appeared in the comments from VR concerts. Considering that the upload times of the two types of videos overlap for a certain period of time, it can be assumed that people have feelings of missing VR concerts. In other words, the assumption of missing things in the previous section is more likely to miss the VR concert rather than the period of the pre-Covid-19 pandemic. This assumption is crucial for comprehending how VR concerts vary from general concert videos, and it will be specifically addressed in the following chapter using dynamic topic modeling that incorporates date metadata.

4.4 Public Opinion Toward VR Concert

This chapter is the main result of the research utilizing BERTopic and Text Regression to investigate the public opinion of the commentary data toward VR concerts. In the first section, I analyzed 11 prominent topics including the largest number of comments clusters. These topics indicate the primary response from viewers to VR concerts. In addition, I selected 3 more topics that reflect the situation of the pandemic period and the remote virtual environment when people enjoy VR concerts. With these 14 topics, I deduced the main themes that show how the latent topics of comments from VR concert videos.

The second section introduces the compound quantitative analysis of the text data. Before this analysis, the comments underwent lexical analysis utilizing the TF-IDF word embedding model and the BERTopic model, resulting in extracting key terms and topics from the textual data. When considering that the topic modeling method is one of the classification methods, this section provides different types of results for further understanding of the viewers by utilizing regression model. Significantly, the objective of this analysis is to combine the themes from topic modeling with numerical data to uncover patterns and trends. Text regression with OLS model was mainly utilized to quantify the impact of categorized corpus on the numerical aspects of the data, such as the number of likes received by each comment and the time that comments are published. This method can identify which terms are most impactful or dynamic among viewers of VR concerts.

4.4.1 Prominent Topics of the Main Data

10,014 comments' worth of data were kept after preprocessing the main data and were utilized to explore the prominent topic. I got 83 topics from the initial results of the topic modeling that at least include more than 30 clusters of embedded sentences. Along with the primary topic representations and the knowledge from the prior descriptive result of the data, I reduce the number of topics by merging related topics which have similar terms together, and consequently, 57 topics are extracted from the main data. All topics and representative terms are attached in Appendix-B.

Table 4-5 Prominent Topic from Main Data

Topic	Count	Term1	Term2	Term3	Term4
0_Marshmello	856	'marshmello',0.0769	'stage',0.0729	'epic',0.058	'map',0.0484
1_Nostalgia	664	'year',0.0968	'ago',0.0728	'nostalgia',0.0635	'memory',0.0548
2_Ariana	567	'ariana',0.1073	'grand',0.0646	'arianas',0.0322	'love',0.0279
3_Best_Event	538	'fortnite',0.0581	'best',0.045	'event',0.0396	'concert',0.031
4_Masterpiece	463	'amaze',0.1088	'masterpiece',0.0886	'cool',0.0671	'best',0.0537
5_Music	442	'song',0.0792	'music',0.0538	'listen',0.039	'world',0.0244
6_Virtual	356	'concert',0.0943	'real',0.0426	'imagine',0.038	'virtual',0.0339
7_Jucie_Wrld	242	'rip',0.1533	'die',0.1507	'world',0.0938	'people',0.0648
8_Old_Map	222	'miss',0.1463	'old',0.0828	'map',0.056	'sad',0.0257
9_Shop	215	'skin',0.2377	'shop',0.0551	'buy',0.0494	'item',0.0429

Table 4-5 (continued)

Topic	Count	Term1	Term2	Term3	Term4
10_Job	199	'job',0.1132	'work',0.0867	'watch',0.0738	'bro',0.0695
11_Mac_Miller	186	'mac',0.1779	'miller',0.1137	'heaven',0.0924	'way',0.0755
52_Metaverse	32	'metaverse',0.5984	'iconic',0.2117	'meta',0.1387	'facebook',0.0991
56_Safe	31	'safe',0.644	'safest',0.3325	'concert',0.1549	'stomp',0.1118
57_Virus	30	'virus',0.1999	'corona',0.1964	'quarantine',0.184	'hold',0.096

Table 4-5 shows the 11 prevalent topics and 3 prominent topics that give indications to comprehend public opinion of VR concerts. The topic column stands for the name of the topic that is assigned based on the term, the count column is the number of embedded sentence clusters organizing the topic, and term columns are the four most frequent terms in the cluster. With the result of merged topic representations, I identify several themes for investigating the current public opinion of VR concerts.

Theme 1: Performers

The first theme is composed of topics related to performers that included topics 0, 2, 7, 10, and 11. In-depth, topic 0 is about DJ Marshmello’s VR concert and can identify that many people enjoyed the concert's virtual setting and stage. Viewers are more receptive to novel visual stimulation compared to other topics dealing with performers because Marshmello’s concert was the first VR concert held in Fortnite, in 2019. Also, the concept of the VR concert was not that widespread compared to the period after the Covid-19 pandemic. Topics 2 and 10 are topics consisting of positive remarks about the artists of the concerts, Ariana Grande and Tavis Scott. It can be found that the writers of the comments use words such as “bro” and “angel” to express their fan love and proximity to singers.

Theme 2: Positive reaction

Topics 3 and 4 organize the theme that reveals strong positivity toward the VR concert. Concretely, topic 4 consists of praising terms, like “amaze”, “masterpiece”, “cool”, and “best”. Topic 3 includes more detailed information about the types of positivity. In topic 3, I can verify that people respond to the VR concert as a live concert beyond the simple promotion of the game through terms such as “event” and “concert”. Interestingly, the term “live” is also ranked as the 9th dominant term of topic 3, so even when people enjoy the recorded video from YouTube, a big portion of the people used the term “live” and consider it as a live concert when they write the comments. Therefore, it can be speculated that people react positively to VR concerts as a form of live concerts.

Theme 3: Platform sensitivity

Meanwhile, from topic 4, the name of the platform, Fortnite, is the most dominant term, and it can be assumed that the platform has a lot of influence on public opinion. In other words, when people write comments to acclaim VR concerts, the majority of them think of those concerts as platforms in conjunction. Topics 8 and 9 robustly support the assumption in the fact that many people write comments for suggestions and complaints on the platform Fortnite. For example, topic 8 is about missing an old version of Fortnite that is updated now since the version when the concert was held, and topic 9 is suggesting for the performer’s avatar be resold in the game. Consequently, VR concerts suggest that consumers may be sensitive to platforms because they are mediated by specific platforms and show new types of consumer behavior that were not detected in conventional concerts.

Theme 4: New Value of VR concert

It is a theme about the new value that arises uniquely in VR concerts according to the technical characteristics of VR concerts. The organization of Topic 11 is primarily based on the comments from the Ariana Grande video, however, Mac Miller who was not the performer at the VR concert came out as the dominant term of this topic. Indeed, Mac Miller is an American rapper who dated Ariana Grande for a few years and died in 2018. In order to fully comprehend this topic, searched up more terms and found *peace*, *rest*, *tribute*, and *rip* in prevalent terms of the topic. With this topic, I can define the new value of a virtual concert, named "perpetuity". Topic 7 "Juice wrld" reconfirms the unique value of the VR concert more robustly because this is the topic about the concert of the American rapper Juice Wrld who already died in 2019, but the concert was held in 2021. Specifically, the Fortnite team held the VR concert with the avatar of Juice Wrld with his unreleased music and so the term "rip" is displayed as the first dominant term of topic 7 in that people commemorate their favorite singers with the VR concert. In the virtual condition, even if the singer died, it is possible to hold a live concert thanks to the development of technology, such as imitation of voice with machine learning technology or embodiment of an avatar with motion copy so that it can create new kind of experiential value of live concert.

The value "perpetuity" is also related to topic 1, "nostalgia". From the representative comments on this topic, surprisingly, I can identify that people miss the period they can enjoy these VR concerts during the Covid-19 pandemic period. For example, comments like "Still remember event", and "Already one year" are representative documents of this topic. I can derive the answers to questions from lexical analysis with TF-IDF word embedding, what period exactly people are missing through these topics. Intuitively, VR live concerts are preserved in digital archives, they have a characteristic of perpetuity, creating a new type of consumer enjoying live concerts who continually watch recorded live concerts or commemorate their favorite singers.

Theme 5: Strengths of VR concert

Theme 5 is about the strengths of VR concerts compared to traditional live concerts. First is that VR concerts can maximize auditory simulation. Particularly, auditory senses like *song*, *music*, *voice*, *beautiful* are the dominant terms organizing topic 5. In an on-site live concert environment, the sound quality of the concert is dependent on various factors, such as the infrastructure or the shape of the stage, the electrical equipment, etc., so it is hard to keep the consistent quality of the auditory stimuli. By contrast, in the context of the online environment, most concerts are pre-recorded or held in the studio, so people can enjoy them in comparably stable conditions. Therefore, it can be analyzed that when consumers enjoy live concerts in remote conditions, they react more sensitively to auditory stimulation than to on-site concerts.

Second, VR concerts provide a safer alternative for enjoying live concerts. Topics 56 and 57 are the representative topics for this strength. Dominant terms of topic 56 directly express the safety issue, but in addition to this, *stomp* is shown as the 4th prevalent term composing the topic. In November 2021, a tragic crowd crash occurred during Travis Scott's live performance in Huston, Texas, caused eight people to pass away in the venue and two more to die after being taken to the hospital. The tragedy was imprinted on many people's minds, leading to comments on Travis Scott's VR concert video and raising awareness about the safety issues of on-site live concerts. Moreover, given that people's awareness of the importance of safety has grown after the Covid-19 pandemic, both for the producers and consumers (Hu et al., 2021), topic 57 sides with the advantage of the safe environment of VR concerts. In fact, topic 57 is mainly about complaints and depressing emotional expressions during the Covid-19 pandemic, however considering that many people enjoyed these videos during the pandemic and that the *virus* is an important topic from clusters of main data, it can be implied that attending an on-site live concert will remind them of the Covid-19 pandemic and personal safety.

Theme 6: Future of live concert

This is the major discovery from the result of the topic modeling for understanding the status of the VR concert. Topics 6 and 52 mainly explain this theme since they are dealing with topics related to the "virtual" and "metaverse". Especially, frequent terms in Topic 6 can reveal deeply what consumers are thinking about VR content. First, the terms *concert*, *real*, and *like* are assigned for the 1st, 2nd, and 6th in the topic, and it shows that people feel a kind of immersive experience being in the VR concert. When associating these terms with the 2nd most popular comment, "Yeah I've been to a Travis Scott concert", it is clearly demonstrated that a host of people feel an immersive sense of being in a live concert even enjoying it in remote conditions.

Furthermore, with other dominant terms, such as *virtual*, *future*, *imagine*, and *life*, I can determine that people who have watched the VR concerts consider it as one of the future lifestyles to enjoy the live concert. Topic 52 goes a step further and shows that people are talking about *metaverse* even though it is recorded VR content in the form of a concert that was already held before the term metaverse became widespread. In conclusion, this theme examines how some people like VR concerts and believe they are one of the future live concert formats that along with the concept metaverse.

4.4.2 Quantitative Analysis of Public Opinions Using Text Regression

(1) Result of Regression with the Likes of Comments and Sentiment Indices: Table 4-6 summarizes the result of Eq (3-9), which verifies H1 if the PSI (or NSI) of comments affects the number of likes on comments positively (or negatively). Model (1) only involved the positive sentiment index (PSI) as the baseline model. The results show that PSI significantly affects the number of likes but in a negative way, so it is consistent with H1. From the result of model (2), which included both PSI and negative sentiment index (NSI) as independent variables, I can detect that both variables significantly affect the number of thumbs up. Moreover, it is uncovered that NSI has a negative impact on the dependent variables, so the other side of H1 is also supported by the model (2).

The result of H1 points out a noteworthy finding that comments written in both positive and negative moods impact negatively the likes of comments. Also, even when comments are written with a positive sentiment, it lessens the number of likes on comments. The reason for these findings can be deduced from the natural characteristics of the sentiment index. The sentiment index is an indicator of how biased a comment's emotions are. Therefore, regardless of whether they are positive or negative, the higher the index is, the more polarized comments are. It means that when comments are written with biased emotions, it is hard to have sympathy with other viewers of the videos.

Table 4-6 Regression result with the likes and sentiment indices

Variables	(1) Log(likes)	(2) Log(likes)
Pos. Sentiment	-0.41***	-0.58***
	(0.07)	(0.08)
Neg. Sentiment		-0.83***
		(0.12)
Constant	1.66***	1.80***
	(0.03)	(0.04)
No. Observations	10013	10013
R-squared	0.003	0.008

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

(2) Result of Regression with the Sentiment Indices and Themes of Comments: Table 4-7 presents two regression models that take themes' possibility in each comment as an independent variable and PSI and NSI as dependent variables respectively. The first model shows that all themes affect PSI and confirms Hypothesis 2. Specifically, "Performers," "Positive reaction," and "Strengths" themes positively affect PSI while "Platform," "Value," and "Future" themes negatively affect PSL. Since "Positive reaction" mostly consists of positive terms as it is by name, its impact is most significant among other themes. Although "Performers" and "Strength" have relatively low coefficients (0.05 and 0.03), they still significantly contribute to PSI's range. The grounds for this value can be discovered from each theme's dominant terms. Although dominant terms in "Performer" have positive sentiments such as *love*, *great*, and *amaze*; it also contains many neutral sentiment terms like *stage*, *map*, or artist's name; hence its coefficient is not counted as high. Similarly, "Strength" consists of topics regarding accidents at live concerts and fans' longing emotions; therefore, its coefficient value is relatively low. Nevertheless, it can be seen from a significant level that both themes' dominant terms and topics are composed of positive words so affects the value of PSI.

Conversely, the themes of "Value" and "Future" have negative coefficient values. The theme of "Value" consists of missing emotion of VR concerts and commemorating dead singers, which can be seen as having more negative sentiments. Likewise, the theme of "Future" is negatively correlated with PSI because dominant words with neutral sentiment such as *concert* and *virtual*, and negative terms such as *quarantine* and *virus* are categorized together. The theme of "Platform" which has the highest coefficient value gives a remarkable point to understand the viewers of VR concerts. Specifically, the theme “Platform” is categorized with the comments that users of Fortnite give opinions and complaints about the platform. Even if this is a concert video, it is shown that when the concert is held on a particular platform, consumers are very sensitive to the platform, and most of them write comments with negative sentiments.

Table 4-7 Regression result of PSI and NSI with Themes

Variables	(1) Pos	(2) Neg
Performers	0.05***	-0.05***
	(0.01)	(0.01)
Positive reaction	0.52***	-0.12***
	(0.01)	(0.01)
Platform	-0.14***	0.08***
	(0.02)	(0.01)
Value	-0.09***	-0.01
	(0.01)	(0.01)
Strengths	0.03***	-0.01
	(0.01)	(0.01)
Future	-0.13***	-0.05***
	(0.02)	(0.01)
Const	0.25***	0.12***
	(0.00)	(0.00)
No. Observations	10013	10013
R-squared	0.198	0.029

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

Since the regression model is composed of the same independent variable and polarized dependent variables, most coefficient values of the Neg model show the opposite sign to model (1). However, themes “Value”, “Strengths” do not significantly affect the value of NSI, so the one of hypothesis 3 from equation (3-11) is rejected. The theme of “Future” has distinctive implications among the coefficient value of statistically significant themes, especially since it negatively related to both PSI and NSI. This suggests that comments related to the “Future” theme are mostly neutral in sentiment rather than positive or negative, so it is unclear to judge how people feel about VR concerts in the form of future live concerts with this result. Therefore, it can be expected that a regression model that analyzes the number of likes and themes in the next section shows which themes people are more empathetic or interested in, enabling further research.

(3) Result of Regression with the Likes of Comments and Themes of Comments: This analysis has great significance for understanding the Public Opinion of VR concerts because it shows not only the viewers who write comments but also the other viewers who interact with them. Considering two hundred million views and a total of 1,435,223 thumbs up on whole comments compared to 10,000 comments, these interactions have great implications for consumers' deep understanding.

Table 4-8 is a table that sorts the results of the regression model corresponding to equation (3-12) by the value of the coefficient. In this model, the dependent variable is the logarithm number of likes. The table shows that Model (1) indicates that the “Platform” and “Value” topics do not have a statistically significant effect on the number of likes, so hypothesis 3 is rejected. To interpret the result that two themes as not statistically significant, although many people talk about the “Platform” and “Value” of VR concerts through comments, these themes are not of great interest to those who are passive in writing comments but do the interaction.

Table 4-8 Regression result with the Number of Likes on Comments and Themes

	(1)	(2)
Variables	Log(likes)	Log(likes)
Performers	1.73***	1.75***
	(0.11)	(0.10)
Future	1.24***	1.26***
	(0.16)	(0.16)
Strengths	1.07***	1.09***
	(0.11)	(0.10)
Positive reaction	-0.41***	-0.39***
	(0.10)	(0.09)
Platform	-0.09	
	(0.13)	
Value	-0.07	
	(0.09)	
Const	1.30***	1.28***
	(0.04)	(0.03)
No. Observations	10013	10013
R-squared	0.043	0.043

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

The model was deemed worth analyzing even though Hypothesis 3 was rejected. Two statistically insignificant themes were subtracted to create a model (2) for more accurate analysis. The “Performers” theme has the highest coefficient value (1.75) among the four significant themes. It is inferred that the traditional live concert value of “Proximity to Singer” has changed in the virtual environment to express interest and empathy toward the performer. Even though performers in the VR concert are graphical avatars and not real humans, most people feel attached to them and think of them as a principal element of the concert. The coefficient value of 1.26 for the theme “Future” in model (2) shows that people are enthusiastic and agree to VR concerts becoming a form of live concerts in the future. This indicates that VR concerts have the potential to develop into evolved or other forms of concerts. The “Strengths” of VR concerts, sensory stimuli, and safety issues are also sympathized with many people. Although the coefficient value is lower compared to the previous two themes, when considering the dependent variable is logarithm value, there is a significant influence on the dependent variable. A coefficient value of 1.09 rises about twice as many likes for each unit of increase in the probability that a comment will consist of a theme of “Strengths”. The negative coefficient value of the "Positive reaction" theme is robustly explained by the fact found in Hypothesis 1 that sentimentally prejudiced comments do not receive much sympathy from others. It can also be deduced that when there is no specific object like performers in comments, viewers are less likely to hold it in high regard even if it is written in a highly positive mood.

(4) Result of Regression with the Published Period of Comments and Themes: In the last part of the regression analysis, I set the period when the comment was written as a dependent variable as a binary variable, dividing it into pandemic and after-pandemic, to see what aspects of the VR concert people are referring to over time. Accordingly, the higher the coefficient of the independent variable, the more likely it was mentioned after the pandemic, and the lower the coefficient, the more likely it was mentioned during the pandemic. Based on the analysis results of the previous H3 model, themes "Performers", "Positive reaction", "Strengths", and "Future" were mainly selected to investigate the tendency of major people.

Table 4-9 Regression Result with the Pandemic Period and Themes

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Period	Period	Period	Period	Period	Period
Performers	-0.24***	-0.24***	-0.23***	-0.20***	-0.22***	-0.23***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Positive reaction		0.10***	0.10***	0.13***	0.11***	0.10***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Platform			0.14***	0.15***	0.13***	0.12***
			(0.03)	(0.03)	(0.03)	(0.03)
Value				0.15***	0.12***	0.11***
				(0.02)	(0.02)	(0.02)
Strengths					-0.16***	-0.17***
					(0.02)	(0.02)
Future						-0.18***
						(0.04)
Const	0.60***	0.58***	0.57***	0.54***	0.57***	0.58***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
No. Observations	10013	10013	10013	10013	10013	10013
R-squared	0.012	0.014	0.017	0.022	0.027	0.029

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

From the result of the regression model in table 4-9, statistically significant coefficient values of the model (6) that composes all themes as independent variables show that the themes of the VR concert video comments vary over time consistent with Hypothesis 4. Among the topics selected for the main target, only the "Positive reactions" theme appears to have positive coefficients. When considering that Twitter's posts are mainly written in negative sentiment in certain situations due to spread of the virus during the Covid-19 pandemic (Kydros et al., 2021), it can be suggested that most viewers who enjoyed the VR concert during the Covid-19 pandemic are also likely to watch the videos while quarantined due to mass gathering restrictions and write the comments in more negative sentiments.

On the other hand, themes “Performers,” “Strengths,” and “Future” tend to be written before the end of the Covid-19 pandemic. The negative coefficient (-0.23) of the theme “Performers” can be inferred that more people talked about performers because concerts by Marsh Mello and Ariana Grande, which account for the largest distribution of the subject, were held at this time. In fact, this theme is more relevant to the time when the concert was held than to the specificity of the pandemic.

Secondly, “Strengths” has a negative coefficient (-0.17) because it is organized with topics related to a field accident at the Travis Scott concert in 2021 and the role in a safe concert adopted by people during Covid-19. Finally, for the “Future” theme, it can be drawn that most VR concerts were held before the Covid-19 pandemic when more people were fascinated by the novelty of VR concerts and called them the future of concerts. From this implication, I can conclude that more people are familiar with enjoying VR concerts and are ready to accept this as a distinctive form of a live concert as time goes on.

This section discusses the findings of a regression analysis on the relationship between the numbers of thumbs up on comments, themes of comments, the period that comments were published, and the sentiment index of video viewers. The regression model of hypothesis 1 shows that it is challenging to empathize with other video viewers when comments appear with skewed sentiments. Second, the dominant terms of each theme play a crucial role in determining the direction of the coefficient values for explaining the values of the sentiment index of each comment. Third, the regression analysis between themes of the comment and the number of likes shows that many people think the performance’s artist is a crucial aspect of the performance. Even the virtual reality avatar has developed a strong bond with followers. Moreover, VR concerts are regarded as a distinctive form of live concerts which has their own strengths, and this opinion draws a lot of interest and sympathy from viewers. Finally, during the Covid-19 epidemic, individuals experienced more VR concerts than they had previously, and they were becoming more accustomed to them.

Table 4-10 Result of the Hypothesis Test of the Text Regression

Hypothesis	Result
$H1$: The number of thumbs up has a significant relationship with the positive (and negative) sentiment index of comments.	Accepted
$H1'$: The number of thumbs up has a positive relationship with the negative sentiment index of comments.	Accepted
$H2$: Themes of the comments significantly affect the PSI of the comment.	Accepted
$H2'$: Themes of the comments significantly affect the NSI of the comment.	Rejected
$H3$: Themes of the comments significantly affect the number of thumbs up on comments.	Rejected
$H4$: Themes of the comments are different in dissimilar periods.	Accepted

4.5 Additional Research with Dynamic Topic Modeling

In this chapter, I studied how topics changed in different conditions by exploiting dynamic topic modeling method. Specifically, I selected notable topics to assess the main purpose of this thesis, such as topics about virtual reality, remote conditions, and topics to find the new value of Virtual concerts different from classical live concerts. For the second section of this chapter, I compare how topics are different from VR concert videos and general concert videos. Since both types of videos share one common feature, remote condition, I aimed to make it clear how VR concerts make viewers feel differently from general concert videos.

4.5.1 Topics Over Time

In order to support some of the analysis results in the previous section and to gain a deeper understanding of public opinion about VR concerts, seven topics were chosen and analyzed together on which changing opinions over time give more insightful information. In detail, topics 1 and topic 57 were selected to figure out the exact longing time that people usually write for the comment. In addition to this topic 57 combined with topic 56 to research how the other strength of the VR concert, "Safety", is developed with the occurrence of the Covid-19 pandemic. Topic 6 and topic 52 which are the representative topics for theme 6 from section 4.4.1, show a more profound understanding of how people started to consider VR concerts as the future form of the live concert. Lastly, topic 7 was selected to investigate if the death of an artist affects the formation of the representative topic.

Figure 4-5 shows seven selected topics and how they are changed over time. First is topic 1 "Nostalgia" to identify if people really miss the VR concerts after the re-opening of the community. The frequency graph obviously proves that people miss the prior period as the frequency had soared since mid-2021 following the lift of social distancing due to Covid-19 and the beginning of on-site live concerts. It is well-known that Covid-19 brings not only physical concerns but also psychological discomfort to individuals (Salari et al., 2020) and topic 57 "Virus" also shows that people concern the Covid-19 till 2021 when they watched the VR concert. Nevertheless, the soaring frequency of "Nostalgia" shows that VR concerts give people time to release their depression and they think of the old days they enjoyed VR concerts in their rooms.

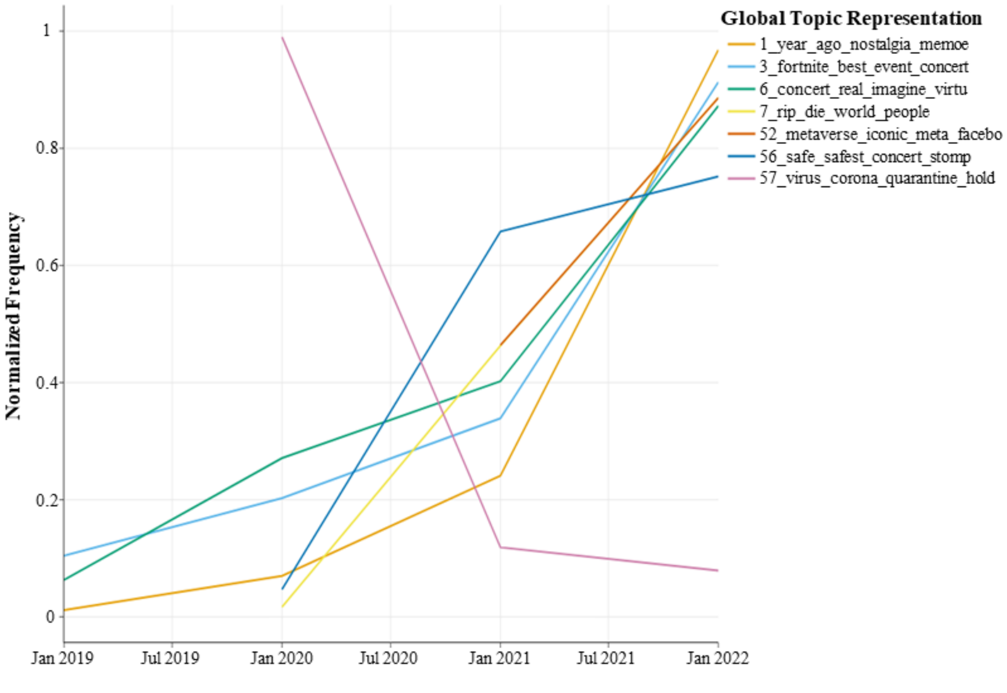

Figure 4-5 Frequency of Selected Topics Over Time

Second, the positive relationship between topic 6 “Virtual” and topic 52 “Metaverse” can be detected from the shape of the graph. Specifically, although the topic “Virtual” was started from the early of the VR concert videos and has been mentioned continuously throughout the whole period, it shows a significant increase when the topic “Metaverse” first came out in 2021. The key terms to explain this phenomenon are “Meta” and “Facebook”. In 2021, Facebook changed its company’s name to Meta and declared that it would earnestly focus on bringing the metaverse to real life. After this astonishing declaration, people’s interest in the metaverse exploded, giving rise to an interest in virtual reality as well. Owing no clear definition of the metaverse till now, it indicates that many people perceive VR as part or itself of the metaverse.

Third, the frequency graph of topics 56 “Safe” and 57 “Virus” represents a concern about safety issues after the outbreak of Covid-19. Following the Covid-19 outbreak, safety concerns have become a significant factor when people attend mass gathering events like live concerts, as shown by the nearly opposite trajectories in these two graphs. Despite the downward trend of the frequency of the topic “Safe” after 2021 with the emerge of the Omicron variant, several people still mentioned this topic and VR concerts would be considered as the proper alternative for them.

From topic 7, “Juice Wrld”, I find that the topic is displayed from 2020 and sharply increased till 2022. Through this trend, I can identify that this topic includes a small portion of comments related to the death of others, such as Mac Miller or the victim of a crushing death at Travis Scott’s concert. However, still, the majority of the period is concentrated toward 2022, I perorate that this topic doesn’t show significant information with the trend graph. In addition, regarding the trend of topic 3 which indicates strong positivity toward VR concerts, meaningful changes were not found when considering the number of comments each year.

Overall, I can confirm that many people miss the VR concert after the Covid-19 pandemic even though that period caused them physical and mental difficulties. Moreover, people’s attention to the VR concert was continuous since it was first held in 2019, but after the launch of Meta, the concentration increased significantly and some of them consider VR concerts as part of the metaverse. Finally, it is clear that people worry about the safety of mass gathering and concert during the Covid-19 pandemic, therefore VR concert has an outstanding advantage in the sense of safety issue and can be an alternative for some people in the way of enjoying live concert.

4.5.3 Compare Topic to General Concert Videos

In this section, for the purpose of comparing the topical differences between VR concert videos and general concert videos, all 36,484 comments data are embedded together to get the global topic representation. Then, the term frequency from each class is multiplied by the IDF values calculated in the prior process to get the local topic representation for each class. I obtained 187 global topic representations and selected distinguished topics to compare how people react differently from VR concert videos to general concert videos. Primarily, topics 4, 18, 104, 71, 98, 101, and 133 were adopted that clearly indicate dissimilarity between VR concert videos and general concert videos, in addition, topics 2, 6, 8, 10, 38 are selected for additional research to understand the public opinion of the people when watching live concerts in remote conditions. Global topic representation with terms and local topic representation of those 12 topics are attached in Appendix-C.

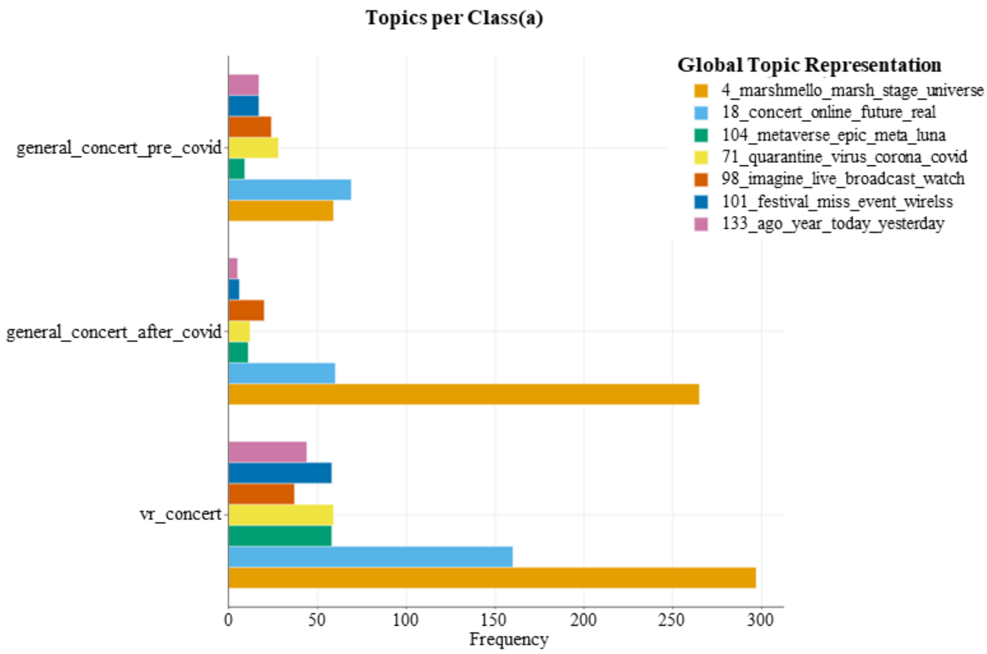

Figure 4-6 Stands Out Topics on VR Concert Videos Compared to General Concert Videos

Figure 4-6 shows topics that notably have a higher frequency in VR concert videos rather than in general concert videos. First, from topic 4, although two classes share the same key term and have a similar frequency, I discover that local topic representation deals with slightly different topics and gives insightful information to understand the difference in public opinion between different classes. Table 4-6 shows the main terms of topic 4 for each class and implicates VR concert mainly consisting of the terms related to the stage of the video and general concert video is mainly about the performance. Thus, this different local topic representation manipulates people are more sensitive to visual stimulation when they are watching VR concert videos than general concert videos.

Table 4-10 Local Topic Representation of Topic 4

Topic	Count	Class	Terms
4_Marshmello	265	General Concert After Covid	marshmello, marsh, set, alan, khalid
	297	VR Concert	marshmello, stage, universe, marsh, map

Second, topics 18 and 104 are related to people's expectations of the future form of live concerts. In detail, topic 18 is a topic about their engrossing experience when enjoying the concert videos and talking about the vision of the future of live concerts. Similarly, topic 104 primarily includes the term new technology like *metaverse* which is considered a similar term to VR confirmed in the prior section. The topic frequency from Figure 4-6 robustly illustrates that the proportion of two topics is much higher in VR concerts and therefore numerous people thought about the next generation of live concerts after they watched VR concert videos. Although, topic 98 includes the dominant term *imagine* similar to the prior two topics, however, it is made of with the terms *broadcast* and *watch* which don’t have a marked relationship with the imagination of the future live concert and there is no significant gap in topic frequencies among the three classes. This dissimilar topic frequency supports that imagination of the future is mainly applied to VR concert videos.

Third, the high frequency of topic 71 regarding the *quarantine* and *virus* shows that the VR concert was enjoyed a lot during the Covid-19 pandemic period especially when cities were locked down. Besides, even though people had the option to watch previous performance videos, the frequency of 71 is overwhelmingly higher for the VR concert videos than in other classes. Accordingly, under the special circumstances of the Covid-19 pandemic, VR concerts already have replaced on-site live concerts and are considered the better option for recorded videos. This fact suggests that VR concerts, as well as pandemic-like situations, can be an excellent alternative to on-site live concerts to overcome various problems such as physical problems like disabilities, and spatial limitations caused by underdeveloped infrastructure.

Fourth, the frequency of topics relevant to nostalgic emotion, topics 101 and 103, is remarkably high in the VR concert. It was robustly demonstrated that big amount of people miss VR concerts held during the Covid-19 pandemic in the prior investigation, furthermore, with the comparison of topic frequency among different classes, it is more obviously proved nostalgic emotion mostly appears in VR concert videos. Specifically, the higher frequency of these topics in general videos of the pre-Covid period than in the after-Covid period indicates that people may repeatedly watch old live concert videos in the Covid-19 period. However, the conspicuously low frequency of these topics in the after-Covid video implies that people don’t feel the nostalgic emotion anymore from the recorded videos on YouTube after the on-site concerts were held again. In other words, considering that consumers still miss VR concerts after the community reopened and the on-site live concerts have begun again, VR concerts are a different form of content to consumers than on-site live concerts.

In summary, compared to the general concert videos, topics of VR concert comments are more focused on visual stimulation. Although the topic is talking about the same artist, VR concerts mainly deal with the virtual stage of the video. Furthermore, people tend to think of VR concerts as an advanced direction of live concerts. On the other hand, it has been confirmed that general concert videos are more considered to be recorded live performances. Also, it is proved that VR concerts have already substituted conventional on-site live concerts during the COVID-19 pandemic. Despite it happening under special circumstances, VR concerts are still expected to be an alternative in other uncomfortable situations such as disability and distance from the venue. Finally, it was established that the VR concert had been turned into specified content different from the recorded live concerts. The topic of “Nostalgia,” which is only brought up in the VR concert video's comments exemplifies this point amply with the fact that people miss the VR concert after there are fewer restrictions on mass gatherings after the pandemic.

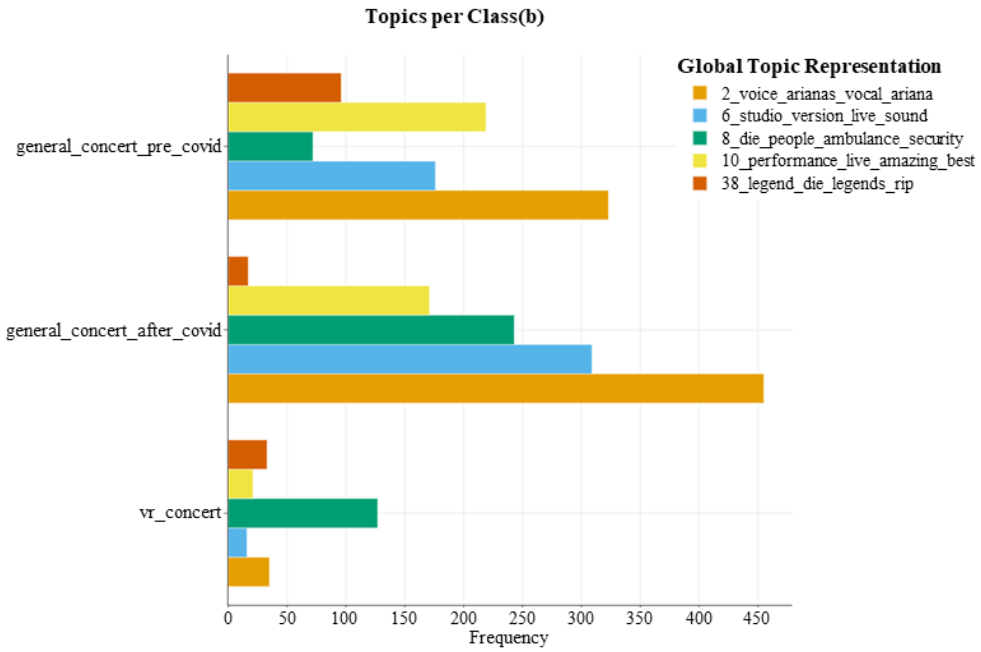

Figure 4-7 Stands Out Topics on General Concert Videos Compared to VR Concert Videos

Figure 4-7 on the other hand, mostly displays selected topics that are more frequent in general concert videos. From the prior Section 4.4.1, topics related to auditory stimulation were one of the frequent topics from the comments of VR concert videos, however, when compared to the general video, the frequency of the topic is markedly low. It can be suggested that people focus on auditory stimulation when they watch a general concert video more than VR concert videos with topic 2. One of the reasons for this tendency is supposed that people already get used to watching recorded videos on YouTube and these videos have no significant difference from real-world scenes and are hard to give visual stimuli to them. Meanwhile, when it comes to virtual worlds, which just started to be popular during the Covid-19 pandemic, people feel more interested in the visual stimulation of new kinds of worlds, stages, avatars, etc. Moreover, in a digitalization environment, live video is one of the audible file options for listening to music, for example, YouTube Music provides a service that converts all YouTube videos into music streaming. This inclination is obviously shown in topic 6 when people compare the song of a live performance to the studio-recorded version of the music. Topic 6 is rarely mentioned in VR concerts and appears a lot in general concert videos. Consequently, it can be observed that more people discuss auditory stimuli for the general concert videos because they are not only visual material but also auditory materials for certain consumers.

Second, it was discovered that watching general concert videos makes individuals pay closer attention to the performance itself. Specifically, Topic 10 is mainly evaluated for performance in the video, and the distribution of the topic is remarkably low in VR concerts compared to other classes. From this fact, I can speculate that VR concert videos are rarely regarded as just recorded live performances. The result of the lexical analysis using the TF-

IDF method in the prior chapter gives an indication of the people's perception of the VR concert video different from recorded live performances. In detail, *event* was the highest TF-IDF score term among the comments, and *experience* is displayed in the word cloud. Thus, a VR concert is considered an event that they experience rather than watching recorded live performances. This perception is manifestly verified by topic 8 from Figure 4-7 and topic "Safe" determined with VR concert comments. Topic 8 is about the death of Travis Scott's live concert, which was mentioned in the previous analysis, and when all the comments from videos are embedded together, they mainly deal with the situation of the death. However, the topic representation "Safe" from VR concert was about the public perception that a VR concert is a safe concert, not mainly about the incident. Also, "Safe" is not counted as the topic representation with whole comments since most sentences regarding safety are locally distributed just in comments of VR concerts. From this fact, I deduce that in the case of VR concert videos, people think that VR concerts are already a variant of conventional live concerts, and therefore it is likely to develop into a way to enjoy the concert rather than a recorded video.

Last, one of the new values found in VR live concerts suggested in this research, "perpetuity" is also appeared in the general live concert videos. Topic 38 is the cluster of sentences that pray for the bliss of Juciy Wrld's dead. Especially, this topic is frequently distributed in comments from general concert videos before the pre-Covid 19 periods and slightly spread in comments from VR concert videos. The reason that the after-Covid19 period rarely has this topic is that the time Juciy Wrld died's, December 2019, and the Covid-19 pandemic period is similar, so there is no more live concert by Juciy Wrld after the Covid-19 pandemic. As both forms of media are digitalized, it is clear that they share the same value in preserving and transmitting live performances via audio and video platforms. However, with the development of technology, it is possible to realize dead singers with graphical figures or compose their voices and songs using machine learning depending on the singer's characteristics in virtual conditions. In conclusion, perpetuity in recorded videos comes from the characteristic of archived video files, on the other hand, VR concerts have a broader definition of perpetuity because it is possible to create new content in the metaverse beyond rewatching past videos.

To sum up, Figure 4-7 focusing more on general concert videos, provides insights, first, people are more sensitive to auditory stimulation when watching general concert videos rather than VR concert videos. This is because they have become accustomed to seeing the real-world scene through recorded videos, and digitalization has made it easier to access live concert videos in the form of music files. As a result, certain topics exhibit the behavior that some people frequently contrast recorded music files with live performances. Second, it turns out that general concert videos are perceived more literally as recorded live performances of singers rather than as a specific event. On the other hand, in the case of VR concerts, people tend to regard them as a different type of content from recorded videos or classical live concerts, such as they are talking about the safety of concerts. Third, both general concert videos and virtual reality concert videos have persistence as a video medium. However, VR concerts have a lot of potential for scaling, persistence in two classes is accepted in a different sense, and virtual reality concerts are better described by the term perpetuity.

5 Conclusion and Limitations

5.1 Conclusion of Study

This is one of the first studies applying the NLP technique to understand the public preference for VR content under the framework of experiential aspect of telepresence, especially VR concerts in this thesis. Based on the understanding of the comments data with descriptive analysis and lexical analysis, this thesis examined the latent topics of 36,484 comments from YouTube videos with the topic modeling method. In detail, three analyses were conducted using BERTopic, and the first is researching public opinion on VR concerts. From 10,014 comments on the VR concert videos, I first got 83 topics and merged similar topics into 57 topics. From the 11 most prevailing topics and 3 additional prominent topics out of 57 topics, I determined 6 themes. Specifically, a tendency to show passionate affection for artists and a positive response to VR concerts were found. Also, it is manipulated that people are sensitive to the platform because VR concerts are held via specific platforms, so the topic reflects the opinions of existing users of the platform. In addition, it can define a unique experiential value that only appears in VR concerts. The technical characteristics that go beyond the physical laws of VR concerts and the characteristics of digitized videos created a new value called “perpetuity”. Along with the value, the strength of VR concerts was demonstrated by the comparison of traditional live concerts. Specifically, VR concerts proved to have an image of a safe concert due to a fatal accident that occurred in an offline concert. Finally, it was observed that many people regard VR concerts as one of the future possibilities of live concerts.

Additionally, with the probability of categorized topics for each comment, I conducted regression analysis by combining textual data with numerical data. Specifically, the number of thumbs up, the positive and negative sentiment index of each comment, and the written period of comments were adopted as the numerical data in this thesis. The results of a regression analysis first demonstrate that when biased attitudes are present in comments, it is difficult to empathize with other video viewers. Besides, the correlation between comment topics and like counts reveal that many individuals believe the performance's artist to be an important component of the performance and is the key factor in increasing the telepresence in VR conditions by interacting with other viewers. Even the virtual reality avatar has formed a close relationship with fans like the real performers. Additionally, VR concerts are seen as a separate type of live concert that has its own advantages. Viewers are very interested in and sympathetic to this idea. Last but not least, during the Covid-19 outbreak, people attended more VR concerts than they had in the past and had grown accustomed to them.

Third, I investigated how outstanding topics change over time through the dynamic topic modeling technique. In particular, with the topic relevant to nostalgia, it is observed that many people miss VR concerts even after the Covid-19 pandemic. This fact demonstrates that dominant people wrote comments expressing their longing emotion for VR concerts, not for the pre-Covid 19 world. Moreover, interest in VR was steady from the first Fortnite VR concert in 2019, but especially after Facebook was renamed Meta in 2021, interest in VR soared, and the terms VR and Metaverse began to be used interchangeably. The tendency of words to be mixed in this way points out the possibility that VR content is being rebranded as metaverse content. Finally, it is proved that the strength of the safety of VR concerts has been further highlighted since the awareness of hygiene rose during and after the Covid-19 pandemic.

Fourth, I divided the YouTube comments into VR concert videos and general concert videos by type and compared each topic by dividing the general concert videos into pre and after-Covid-19 over time. From this comparison, it was determined that people react more sensitively to the visual stimuli of VR concerts even if they watch the performances of the same singer. Secondly, VR concerts were confirmed as one of the great means of replacing live performances during the Covid-19 pandemic, and there was a clear difference in perception from recorded live performances in that people thought of it as an “event”. Judging from the fact that people continue to miss VR concerts after the Covid-19 pandemic compared to general concert videos, it was concluded that VR concerts could be a form of alternative live concerts in the future amid various difficulties such as physical limitations and time limitations. On the other hand, auditory stimulation was found to be more prominent when enjoying general concert videos. This is because some people use general concert videos as a substitute for music files recorded in the studio. Moreover, regarding the safety issue, which is the strength of the VR concert that came out earlier, it was not found in the general concert video. In other words, regular concert videos only provide people with recorded live performances, so it is hardly regarded as a substitute for live concerts. Finally, regular concert videos also tend to be watched permanently by people as they are digital files, but VR concerts have the value of “perpetuity” because the development of technology allows VR concerts to be produced in various ways.

In conclusion, the results of the research draw solid implications for the research objects associated with the framework of the theory of telepresence. First off, this research supports the notion that telepresence experiences are capable of a potent experience of immersion and presence by verifying the positive public perceptions of VR concerts. This is in accordance with the fundamental ideas of the experience Telepresence theory, which illustrates how engaging and compelling virtual worlds are to users, providing them with a stronger sense of being there in a mediated reality. Second, the identification of VR concerts as offering new experiences and values compared to conventional live concerts highlights the potential of telepresence technologies to enhance and extend human experiences. This expands the experiential Telepresence theory's emphasis on the transformational and enriching character of telepresence, where users can interact with virtual surroundings in new and meaningful ways that hadn't been previously conceivable. Additionally, the acceptance of VR concerts as a form of future live performance shows how telepresence theory is developing. It shows that telepresence technologies are evolving and could reshape the live music industry by enabling individuals to engage in immersive interactions within virtual reality settings. Last, the case of VR concerts partially displacing normal concerts during the Covid-19 pandemic and the acceptance of VR concert videos as a different form from general concert videos suggest the potential for telepresence experiences to replace or enhance traditional live events.

5.2 Academic Implication of Study

In the following respects, this study contributes to existing literature. First, this study identified the strengths and new experiential values of VR concerts that are distinctive from conventional on-site live concerts by searching latent topics of 37,827 comments from YouTube videos. Specifically, it turned out that a VR concert is recognized as a safe concert from dangerous environments such as infection or suffocation because it does not need to gather large crowds in a specific space. In addition, it was found that using computer graphics to organize virtual worlds, stages, and concerts provides people with fresh visual impulses that have never been seen in the real-world. The unique value of VR concerts with the advancement of technology has become apparent as well. In detail, in a VR environment, people can not only watch the performance of singers continuously after their death but also set up a stage with dead singers' avatars and create new concerts with them. Therefore, it has the remarkable value of providing the performances of people's favorite singers forever.

Second, there hasn’t been any research that compared consumer perceptions before and after Covid-19 in terms of engaging with VR content. In this study, furthermore, the possibility of live concerts on the metaverse could be clarified by tracking changes in public opinion over time when enjoying VR concerts and comparing general concert videos. Intuitively, interest in VR concerts has been steadily increasing, and this interest has increased significantly since 2021. The word “virtual reality” is expected to become more attractive to consumers as it begins to rebrand with the advent of the metaverse. Moreover, although both VR concert videos and general concert videos are watched in a remote environment, people feel more sense of enjoying an event at VR concerts. Lastly, since there have been several VR concerts held over the past few years, especially during the Covid-19 period, people are starting to use the word "future" less frequently after the Covid-19 period, which suggests that people have become habituated to them. It was clear that VR concerts replaced conventional on-site live concerts during the Covid-19 period, which is estimated that many people will perceive VR concerts as a proper alternative when other difficulties arise personally or in the future.

Third, this is the first thesis researching the perception of consumers toward VR content using unstructured text data. It is proved that exploring latent pattern using topic modeling give informative insight into other industries, such as tourism and marketing, to understand the consumer (Park et al., 2020; Whang et al., 2021), but it has not been exploited in the live music industry. In this study, comments from VR concert videos uploaded on YouTube, which are regarded as reviews of VR concerts, were used as the main data. As a result, latent topics discovered along with the metadata allowed us to figure out how viewers perceived VR concerts, how few notable perceptions changed over time, and how people differently react to VR concert videos and conventional recorded live concerts.

5.3 Managerial Implication of Study

In a recent internet-evolved environment, comments data is useful data to make optimized business strategies. From the analysis of public opinion toward VR concerts with the comments data from YouTube, this thesis gives the following implications for the possibility and future anticipation of metaverse content. First, awareness of metaverse content has existed for a long time as VR content, but recently, the term VR has been redefined as it has begun to be mixed with metaverse. The reason that VR content is interchangeable with metaverse content at this stage is presumed to be due to the visual part of the metaverse, however, concepts such as cryptocurrency and NTF have not yet been considered together. In other words, despite consumers' favorable opinions of VR entertainment, it must progress beyond audio-visual leisure and suggests that a business model is required in conjunction with the other core ideas of the metaverse.

In addition, it is evidently discovered that people perceive VR concerts as different content from traditional concerts based on the contrast in topics between general concert videos and VR concert videos. In other words, consumers are likely to seek a different value from VR concerts than they would from traditional live shows. In this research, it was revealed that people mainly pursue the safe environment of the VR concert, the spectacular graphics of the metaverse concert, and the production of novel content using elements that are not already present in the real-world.

Finally, VR concerts clearly tend to be thought of as one of the future forms of live concerts. This was confirmed in the video of VR concert videos where many people commented using the word *future*, suggesting that the VR concert will serve as a great alternative, at least in special circumstances, although it is unclear whether it can replace the on-site live concert at this point. In fact, during the Cpvod-19 pandemic, VR concerts already took the role of substitutes for on-site live concerts. Even after on-site live concerts restart after mid-2021, continuous sentiments of nostalgia for VR concerts support this speculation. Therefore, consumers are expected to be able to accommodate VR content, especially after Covid-19, and since there are no significant quick starters of preoccupying the VR content market after the reopening of society, it can be concluded that it is necessary to preoccupy the pioneer's position by developing VR content.

5.4 Limitations and Future Research Directions

Although more than 30,000 comments were used to define the public opinion of VR content, the number of comments is significantly lower than the total views of videos, so they can not represent all viewers who enjoyed the concert videos. Additionally, data is not gathered from the randomly sampled videos but is from concerts held via the singular platform, Fortnite. Therefore, comment data is not representative of all VR concert videos from YouTube. Lastly, since the data was gathered at the end of 2022, the comments are still updated. Thus, there is a possibility that the result of the topic modeling could be changed in the future.

This research has been made possible by the development of technology to understand unstructured text data. However, the main dataset analyzed in this thesis is the YouTube comments that were already written in the past. It is possible to get real-time comments or conversations in the virtual reality world. Real-time comments when people enjoy VR concerts will indicate more directly expressed responses to the VR content and allow us to have a deeper understanding of consumers. Moreover, recently, YouTube has had a solid position as a video platform, and many companies are advertising through it. Therefore, through the methodology of this thesis, the scope of analyzing public opinion can be expanded not only to VR concerts but also to other VR-related content.

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Appendix

Appendix-A Information of the Data Source

Video Name	Number of Views	Uploaded Date	Number of Comments	Type
Travis Scott and Fortnite Present: Astronomical Full Event Video	197,980,542	2020-04-26	5,140	vr_concert
Marshmello Holds First Ever Fortnite Concert Live at Pleasant Park	62,605,389	2019-02-02	1,379	vr_concert
FortnitePresents:RiftTourFeaturingArianaGrande	7,827,613	2021-08-07	1,387	vr_concert
FortnitexArianaGrandeFULLEVENT!	3,650,293	2021-08-06	1,187	vr_concert
FortniteJuiceWrldConcertFullEvent	2,126,638	2022-09-10	1,327	vr_concert
[FULLHD]TravisScottLIVEatACLFest2018w/MikeDeanAustinCityLimitsWeekend1	12,805,287	2018-10-08	1,312	general_concert_pre_covid
[HD720p]TravisScottLive@MadeInAmericaFestival2019FULLSET	346,150	2020-08-14	138	general_concert_pre_covid
TravisScott-FullSetRollingLoudNYC2019	91,304	2019-10-12	35	general_concert_pre_covid
[FULLSET]TravisScottLIVEatMawazineFestival2019 Rabat,Morocco[LQ]	463,264	2019-06-27	402	general_concert_pre_covid
TravisScottRollingLoudMiami2019FULLSET	15,443	2019-05-11	9	general_concert_pre_covid
TravisScott-SickoModeReading+Leeds2018	2,416,161	2018-08-24	249	general_concert_pre_covid
TravisScott-LiveatGOVBALL2018FullSet	3,514,527	2020-06-25	954	general_concert_pre_covid
TravisScott-LiveatReadingFestival2018FullSet	25,813	2021-07-30	15	general_concert_pre_covid
[FULLSET]TravisScottLIVEatLifeIsBeautifulFestival2018LasVegas	374,776	2018-09-23	260	general_concert_pre_covid
TravisScottLIVEfromLollapaloozaonRedBullTV	2,457,254	2018-08-02	981	general_concert_pre_covid
[HD720p]TravisScottLive@MadeInAmericaFestival2019FULLSET	346,151	2020-08-14	138	general_concert_pre_covid
50,000TurnOutInManchesterForArianaGrandeBenefitConcert|NBCNightlyNews	387,443	2017-06-05	167	general_concert_pre_covid
ArianaGrande-GodisaWomanArianaGrandeAtTheBBC	18,605,482	2018-10-29	1,302	general_concert_pre_covid
ArianaGrande-GodisawomanLiveonTheMTVVMAs/2018	34,613,527	2018-08-24	1,255	general_concert_pre_covid
ArianaGrande-OneLastTimeOneLoveManchester	39,068,078	2017-06-04	1,319	general_concert_pre_covid
ArianaGrande-LiveAtAmazonPrimeday2018FULLPERFORMANCE HD	426,594	2018-07-12	124	general_concert_pre_covid
ArianaGrande-BreathinLiveonEllen/2018	18,129,865	2018-11-12	1,310	general_concert_pre_covid

Appendix-A (continued)

Video Name	**Number of Views**	**Uploaded Date**	**Number of Comments**	**Type**
ArianaGrande-NoTearsLeftToCryLiveOnTheTonightShowStarringJimmyFallon	10,370,982	2018-05-24	3,500	general_concert_pre_covid
MarshmelloliveatUltraEurope2018-HD	464,245	2018-09-15	191	general_concert_pre_covid
Marshmello@UltraEurope2018	356,903	2018-07-09	223	general_concert_pre_covid
Marshmello,SelenaGomez-WolvesLiveUltraMusicFestival2018	173,074	2018-03-24	37	general_concert_pre_covid
JuiceWRLDFullLivePerformanceAtLowlandsFestival2019	821,889	2020-08-25	564	general_concert_pre_covid
JuiceWRLD-CampFlogGnaw2019FullSet	496,181	2020-12-28	444	general_concert_pre_covid
JuiceWRLDLiveFullConcert2020	65,682	2020-01-02	54	general_concert_pre_covid
JuiceWrld-RollingLoudNewYork2019	242,804	2020-05-27	167	general_concert_pre_covid
JuiceWRLD-CampFlogGnaw2019FullSet	496,182	2020-12-28	444	general_concert_pre_covid
JuiceWRLD-LucidDreamsJimmyKimmelLive!/2018OfficialVideo	14,146,368	2018-08-08	1,399	general_concert_pre_covid
JuiceWRLD-RobberyLive@MadeinAmericaFestival2019	557,097	2021-08-06	231	general_concert_pre_covid
TRAVISSCOTT-ASTROWORLDFESTIVAL2021-UTOPIA-HOUSTONTEXAS[FULLSHOW/FULLHD]	4,297,890	2021-11-06	1,318	general_concert_after_covid
TravisScottLiveAt@RollingLoud2021NYC	65,744	2022-05-24	47	general_concert_after_covid
FuturebringsoutTravisScotttopreformatRollingLoudMiami2022![FULLVIDEO]Noautotune	170,368	2022-07-23	125	general_concert_after_covid
TRAVISSCOTT-ROLLINGLOUDFULLSETMIAMI2021	324,649	2021-07-25	174	general_concert_after_covid
TravisScottxDrake-KnifeTalk,TSU,N2Deep,Way2Sexy,SickoModeAstroworldFestival2021	374,159	2021-11-06	287	general_concert_after_covid
TravisScott&DrakeSICKOMODE[FULLHD]ASTROWORLDFEST2021	81,992	2021-11-05	26	general_concert_after_covid
TravisScott-MAFIALivePerformanceAstroworld2021	179,824	2021-11-16	138	general_concert_after_covid
TravisScottRollingLoudNYCLive2019fullset	5,998	2019-10-13	4	general_concert_after_covid
TravisScott-LiveatGOVBALL2018FullSet	3,514,403	2020-06-25	954	general_concert_after_covid
ArianaGrandeLiveFullConcert2021	20,223	2021-01-03	10	general_concert_after_covid

Appendix-A (continued)

Video Name	**Number of Views**	**Uploaded Date**	**Number of Comments**	**Type**
TheWeeknd&ArianaGrande–SaveYourTearsLiveonThe2021iHeartRadioMusicAwards	159,746,592	2021-06-01	1,263	general_concert_after_covid
ICONICperformance:ArianaGrande-2022LiveEMAFull4K	49,798	2022-07-18	18	general_concert_after_covid
unseenperformance:ArianaGrandeFullPerformance2022GRAMMYs	915,413	2022-04-04	172	general_concert_after_covid
ArianaGrandeLiveFullConcert2021	20,223	2021-01-03	10	general_concert_after_covid
ArianaGrande-PositionsAlbumOfficialLivePerformances	25,070,771	2021-10-30	1,305	general_concert_after_covid
ArianaGrande-povOfficialLivePerformance|Vevo	34,111,407	2021-06-21	1,317	general_concert_after_covid
ArianaGrande-safetynetft.TyDolla$ignOfficialLivePerformance|Vevo	18,145,021	2021-07-07	1,292	general_concert_after_covid
unseenperformance:ArianaGrandeFullPerformance2022GRAMMYs	915,413	2022-04-04	172	general_concert_after_covid
ArianaGrandeLiveFullConcert2021	20,223	2021-01-03	10	general_concert_after_covid
ArianaGrande-PositionsAlbumOfficialLivePerformances	25,070,771	2021-10-30	1,305	general_concert_after_covid

Appendix -B Topics and Dominant Terms from Main Data

Topic	Count	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7	Term 8	Term 9	Term 10
0_marshmello_stage_epic_map	856	'marshmello',0.0769	'stage',0.0729	'epic',0.058	'map',0.0484	'want',0.0346	'effect',0.0283	'yes',0.0281	'universe',0.0253	'use',0.0229	'game',0.0214
1_year_ago_nostalgia_memory	664	'year',0.0968	'ago',0.0728	'nostalgia',0.0635	'memory',0.0548	'remember',0.052	'old',0.037	'believe',0.0348	'day',0.0312	'nostalgic',0.0309	'month',0.0267
2_ariana_grand_arianas_love	567	'ariana',0.1073	'grand',0.0646	'arianas',0.0322	'love',0.0279	'rift',0.0215	'tour',0.0209	'ink',0.0173	'woman',0.0167	'angel',0.0152	'fan',0.0152
3_fortnite_best_event_concert	538	'fortnite',0.0581	'best',0.045	'event',0.0396	'concert',0.031	'play',0.0144	'like',0.0133	'time',0.0127	'far',0.0127	'make',0.0124	'live',0.0122
4_amaze_masterpiece_cool_best	463	'amaze',0.1088	'masterpiece',0.0886	'cool',0.0671	'best',0.0537	'god',0.0431	'beautiful',0.0383	'incredible',0.037	'event',0.0328	'perfect',0.026	'concert',0.0217
5_song_music_listen_world	442	'song',0.0792	'music',0.0538	'listen',0.039	'world',0.0244	'sing',0.0233	'voice',0.0215	'favourite',0.0193	'beautiful',0.0188	'singer',0.0149	'like',0.0145
6_concert_real_imagine_virtual	356	'concert',0.0943	'real',0.0426	'imagine',0.038	'virtual',0.0339	'future',0.0247	'life',0.0214	'like',0.0214	'ticket',0.0211	'make',0.0161	'felt',0.0141
7_rip_die_world_people	242	'rip',0.1533	'die',0.1507	'world',0.0938	'people',0.0648	'survive',0.0496	'concert',0.0489	'death',0.0407	'lose',0.0357	'disable',0.0273	'family',0.0257
8_miss_old_map_sad	222	'miss',0.1463	'old',0.0828	'map',0.056	'sad',0.0257	'fortnite',0.0254	'think',0.0253	'remember',0.019	'event',0.0185	'year',0.0174	'bring',0.0172
9_skin_shop_buy_item	215	'skin',0.2377	'shop',0.0551	'buy',0.0494	'item',0.0429	'oil',0.0359	'bring',0.0351	'return',0.0316	'wait',0.0301	'come',0.0245	'need',0.0215
10_job_work_watch_bro	199	'job',0.1132	'work',0.0867	'watch',0.0738	'bro',0.0695	'mix',0.0533	'great',0.0484	'crazy',0.0464	'effort',0.0381	'talented',0.0377	'amaze',0.0366
11_mac_miller_heaven_way	186	'mac',0.1779	'miller',0.1137	'heaven',0.0924	'way',0.0755	'legend',0.0642	'stair',0.0552	'walk',0.0449	'transition',0.0333	'peace',0.0329	'rest',0.0313
12_love_event_blow_absolutely	171	'love',0.2279	'event',0.0429	'blow',0.0216	'absolutely',0.0175	'soon',0.0172	'awesome',0.0172	'live',0.0162	'cousin',0.0161	'small',0.0155	'wow',0.0155
13_laugh_loud_grin_glass	165	'laugh',0.2332	'loud',0.1668	'grin',0.086	'glass',0.0844	'big',0.0474	'laughing',0.0404	'scream',0.0392	'funny',0.0256	'mic',0.0244	'useless',0.0186
14_tear_start_end_make	111	'tear',0.1819	'start',0.0755	'end',0.0583	'make',0.0497	'cried',0.0468	'shed',0.0451	'eye',0.0396	'gonna',0.0388	'way',0.0349	'break',0.033
15_goosebump_goosebumps_transition_time	103	'goosebump',0.4049	'goosebumps',0.0943	'transition',0.0563	'time',0.0499	'drop',0.0442	'start',0.0418	'shit',0.0302	'stargaze',0.029	'play',0.0254	'sick',0.0246
16_play_fortnite_admit_fan	101	'play',0.0858	'fortnite',0.0745	'admit',0.0484	'fan',0.0448	'gotta',0.0446	'hate',0.0395	'comment',0.0318	'cool',0.0314	'ism',0.0272	'pretty',0.0262
17_smiley_happy_confusion_replay	98	'smiley',0.3084	'happy',0.253	'confusion',0.0592	'replay',0.0317	'chase',0.0317	'smirk',0.0284	'color',0.0284	'flashback',0.0252	'check',0.0249	'wink',0.0221
18_history_game_best_event	95	'history',0.1987	'game',0.0785	'best',0.0587	'event',0.0522	'gaming',0.03	'definitely',0.0274	'moment',0.0246	'fortnite',0.0217	'culture',0.0209	'watch',0.0187
19_hit_hard_best_cap	94	'hit',0.3048	'hard',0.1455	'best',0.1107	'cap',0.1016	'ground',0.0583	'easy',0.0552	'kick',0.0539	'remain',0.0539	'different',0.0512	'bro',0.0512
20_video_stream_yahoo_copyearight	88	'video',0.302	'stream',0.0471	'yahoo',0.0406	'copyearight',0.0389	'youtube',0.0365	'good',0.0313	'camera',0.0306	'satanic',0.0306	'music',0.0288	'amaze',0.0276
21_fortnite_add_fun_want	84	'fortnite',0.1206	'add',0.072	'fun',0.0624	'want',0.0484	'join',0.0442	'volta',0.0435	'contact',0.0368	'queen',0.0354	'pro',0.0344	'guess',0.029

Appendix -B (continued)

Topic	Count	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7	Term 8	Term 9	Term 10
22_hire_guy_animator_animation	82	'hire',0.1614	'guy',0.1075	'animator',0.0685	'animation',0.0552	'epic',0.0491	'visuals',0.0448	'deus',0.0383	'developer',0.0356	'make',0.0329	'money',0.0327
23_game_happen_sad_cooler	80	'game',0.1355	'happen',0.063	'sad',0.0588	'cooler',0.0578	'sqq',0.0568	'play',0.0558	'eliminate',0.053	'antidote',0.053	'player',0.0524	'white',0.0465
24_dry_frown_pouting_sad	78	'dry',0.2714	'frown',0.2612	'pouting',0.2506	'sad',0.207	'pout',0.0583	'miss',0.0562	'old',0.027	'worthy',0.0265	'liking',0.0251	'pity',0.0241
25_burn_flame_free_bomb	78	'burn',0.1888	'flame',0.1188	'free',0.0932	'bomb',0.0672	'end',0.067	'smoke',0.0642	'ash',0.0629	'pop',0.0541	'fog',0.0499	'pvt',0.0499
26_wish_real_hope_relive	77	'wish',0.3243	'real',0.0592	'hope',0.0558	'relive',0.0419	'dream',0.0367	'scene',0.0319	'event',0.0306	'time',0.0294	'dam',0.0267	'come',0.0238
27_mode_sicko_stargaze_room	75	'mode',0.2949	'sicko',0.2944	'stargaze',0.1991	'room',0.1464	'goosebump',0.1252	'high',0.1222	'confusion',0.075	'drake',0.0745	'intro',0.0629	'sick',0.0423
28_add_need_come_plus	69	'add',0.2392	'need',0.1218	'come',0.0946	'plus',0.0896	'id',0.0829	'goat',0.0726	'bring',0.0701	'added',0.0684	'send',0.0566	'bro',0.0515
29_game_kid_concert_epic	61	'game',0.0886	'kid',0.0599	'concert',0.042	'epic',0.0381	'video',0.0295	'high',0.025	'gaming',0.0244	'jar',0.0201	'like',0.0201	'good',0.0199
30_lit_tough_sane_cage	61	'lit',0.404	'tough',0.1163	'sane',0.1038	'cage',0.1038	'clover',0.1001	'send',0.0779	'thing',0.0706	'luke',0.0685	'light',0.0681	'song',0.0595
31_kid_guy_girl_fortnite	54	'kid',0.1516	'guy',0.1257	'girl',0.101	'fortnite',0.0684	'astronaut',0.0611	'org',0.0563	'hey',0.0497	'old',0.0487	'random',0.0447	'brianna',0.0335
32_galactic_astronomical_galaxy_star	53	'galactic',0.2966	'astronomical',0.2507	'galaxy',0.1637	'star',0.0923	'big',0.0628	'stargaze',0.0576	'stage',0.0546	'chat',0.041	'pull',0.041	'enter',0.0402
33_fan_big_crush_org	51	'fan',0.3115	'big',0.1601	'crush',0.1229	'org',0.0793	'mega',0.0685	'giant',0.0581	'care',0.0575	'huge',0.0531	'love',0.0485	'mummy',0.0382
34_fortnite_come_good_shop	50	'fortnite',0.0903	'come',0.0829	'good',0.0532	'shop',0.0432	'lot',0.0424	'ruin',0.04	'item',0.0399	'plus',0.0393	'store',0.039	'trash',0.039
35_word_censor_bedroom_swear	49	'word',0.2185	'censor',0.2071	'bedroom',0.1961	'swear',0.1561	'bitch',0.1001	'sensor',0.0987	'bleep',0.0987	'whistle',0.0721	'cuss',0.0709	'position',0.0644
36_dream_astr_lucid_vibe	48	'dream',0.19	'astr',0.183	'lucid',0.1506	'vibe',0.0959	'world',0.0771	'wake',0.0531	'pursues',0.0428	'die',0.0414	'demonic',0.0399	'sleep',0.035
37_event_def_fax_beat	47	'event',0.1315	'def',0.0892	'fax',0.0846	'beat',0.0762	'dog',0.0696	'level',0.0582	'lace',0.0562	'celebration',0.0562	'wannabe',0.0562	'animal',0.0562
38_emote_drake_extent_action	47	'emote',0.3449	'drake',0.2194	'extent',0.1668	'action',0.1251	'ring',0.0887	'emotes',0.0816	'dance',0.0469	'need',0.0422	'cringe',0.041	'line',0.0404
39_injury_mosh_pit_int	47	'injury',0.509	'mosh',0.509	'pit',0.4652	'int',0.1763	'age',0.156	'seriously',0.0473	'aged',0.0465	'say',0.0315	'line',0.0305	'predicted',0.0259
40_shoe_nike_jordan_talk	47	'shoe',0.3254	'nike',0.2531	'jordan',0.2255	'talk',0.0993	'wear',0.0988	'foot',0.0741	'tall',0.0741	'head',0.0725	'sneaker',0.0641	'symbol',0.0544
41_chapter_season_pleasant_park	45	'chapter',0.4845	'season',0.3028	'pleasant',0.0575	'park',0.0533	'slowly',0.0501	'island',0.0466	'switch',0.0398	'best',0.0369	'generally',0.0315	'today',0.0283
42_org_axe_tiki_pow	41	'org',0.6611	'axe',0.1093	'tiki',0.0719	'pow',0.0719	'boohoo',0.0719	'col',0.0719	'brew',0.0719	'blind',0.0645	'controller',0.0601	'site',0.0601
43_rapper_kid_favourite_boy	40	'rapper',0.3009	'kid',0.0859	'favourite',0.0806	'boy',0.0769	'childhood',0.0753	'gangster',0.0652	'eminem',0.0533	'baby',0.0428	'rap',0.0428	'child',0.0428

Appendix -B (continued)

Topic	Count	Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7	Term 8	Term 9	Term 10
44_hand_love_french_mush	37	'hand',0.3432	'love',0.1625	'french',0.0904	'mush',0.0904	'proportionally',0.0904	'watt',0.0904	'tendance',0.0904	'spar',0.0904	'galactose',0.0904	'best',0.0894
45_like_light_bullet_beet	35	'like',0.2481	'light',0.1304	'bullet',0.1045	'beet',0.1045	'payed',0.1045	'photon',0.1045	'seller',0.1045	'adorable',0.1045	'trap',0.0937	'terrify',0.0937
46_sick_bro_event_brother	35	'sick',0.1453	'bro',0.1246	'event',0.0594	'brother',0.0566	'cube',0.0448	'zero',0.0406	'cooler',0.0384	'middle',0.0384	'tb',0.0384	'try',0.0377
47_live_event_best_television	34	'live',0.2536	'event',0.0658	'best',0.0485	'television',0.036	'kin',0.0322	'chair',0.0322	'otherworldly',0.0322	'sickest',0.0322	'phase',0.0301	'rock',0.0301
48_song_barry_love_pal	33	'song',0.1707	'barry',0.1658	'love',0.1602	'pal',0.0703	'eternally',0.0523	'tube',0.0523	'diorama',0.0523	'briggs',0.0523	'covey',0.0523	'thee',0.0523
49_event_like_collision_exeter	33	'event',0.103	'like',0.085	'collision',0.0614	'exeter',0.0614	'arenas',0.0614	'separate',0.0614	'actual',0.0582	'rub',0.055	'fracture',0.055	'pretty',0.0527
50_ism_surprise_fan_channel	33	'ism',0.3996	'surprise',0.0767	'fan',0.0628	'channel',0.0615	'lip',0.0478	'lets',0.0478	'rebel',0.0478	'wide',0.0478	'purple',0.0478	'spike',0.0478
51_butterfly_cut_effect_room	33	'butterfly',0.1657	'cut',0.1249	'effect',0.1139	'room',0.1109	'high',0.1042	'underwater',0.0856	'water',0.0721	'end',0.0709	'cubic',0.0631	'ocean',0.0595
52_metaverse_iconic_meta_facebook	32	'metaverse',0.5984	'iconic',0.2117	'meta',0.1387	'facebook',0.0991	'hurry',0.0991	'symbolism',0.0924	'vote',0.0661	'come',0.0633	'magical',0.0578	'humanist',0.0553
53_time_miss_want_fez	32	'time',0.2633	'miss',0.1346	'want',0.0742	'fez',0.069	'satisfaction',0.069	'medic',0.069	'revetment',0.069	'rewind',0.0618	'yonder',0.0577	'homie',0.0577
54_good_nah_man_know	32	'good',0.8022	'nah',0.0978	'man',0.0447	'know',0.0442	'',0	'',0	'',0	'',0	'',0	'',0
55_chill_lao_soul_censor	31	'chill',0.6383	'lao',0.185	'soul',0.0726	'censor',0.0601	'snack',0.0587	'reap',0.0587	'sow',0.0587	'shit',0.0552	'alternative',0.0491	'count',0.0491
56_safe_safest_concert_stomp	31	'safe',0.644	'safest',0.3325	'concert',0.1549	'stomp',0.1118	'safety',0.1061	'prop',0.0813	'afraid',0.06	'train',0.06	'deadly',0.0559	'safer',0.0559
57_virus_corona_quarantine_hold	30	'virus',0.1999	'corona',0.1964	'quarantine',0.184	'hold',0.096	'covid',0.095	'cancel',0.085	'beer',0.0738	'concert',0.0698	'celebrity',0.0474	'perform',0.0473
58_look_goofy_face_ash	30	'look',0.3475	'goofy',0.1723	'face',0.09	'ash',0.0715	'hopefully',0.0701	'cute',0.0607	'cult',0.0567	'jenner',0.0567	'kane',0.0567	'isaac',0.0567

Appendix-C Global Topic Representation with Dominant Terms and Local Topic Representation of Prevalent Topics

Topic	Frequency	Class	Term 1	Term 2	Term 3	Term 4
4_marshmello_marsh_stage_universe	265	general_concert_after_covid	marshmello	marsh	set	alan
	59	general_concert_pre_covid	marshmello	funk	remix	flash
	297	vr_concert	marshmello	stage	universe	marsh
18_concert_online_future_real	60	general_concert_after_covid	concert	ticket	want	jazz
	69	general_concert_pre_covid	concert	wanna	lit	ticket
	160	vr_concert	concert	royal	future	battle
104_metaverse_epic_meta_luna	11	general_concert_after_covid	epic	grail	metaverse	patti
	9	general_concert_pre_covid	epic	metaverse	cocci	luna
	58	vr_concert	metaverse	epic	meta	sci
71_quarantine_virus_corona_covid	12	general_concert_after_covid	quarantine	covid	virus	corona
	28	general_concert_pre_covid	quarantine	virus	corona	covid
	59	vr_concert	quarantine	virus	corona	covid
98_imagine_live_broadcast_watch	20	general_concert_after_covid	imagine	broadcast	online	wish
	24	general_concert_pre_covid	imagine	live	wish	known
	37	vr_concert	imagine	saw	real	psi
101_festival_miss_event_wireless	6	general_concert_after_covid	festival	wireless	paralyse	josh
	17	general_concert_pre_covid	festival	wireless	miss	australian
	58	vr_concert	event	miss	festival	hype
133_ago_year_today_yesterday	5	general_concert_after_covid	ago	year	ticket	post
	17	general_concert_pre_covid	ago	year	today	yesterday
	44	vr_concert	ago	year	today	yesterday
2_voice_arianas_vocal_ariana	455	general_concert_after_covid	voice	arianas	vocal	ariana
	323	general_concert_pre_covid	voice	arianas	vocal	ariana
	35	vr_concert	voice	visuals	arianas	speaker
6_studio_version_live_sound	309	general_concert_after_covid	studio	version	live	sound
	176	general_concert_pre_covid	studio	version	live	sing
	16	vr_concert	version	studio	record	live
8_die_people_ambulance_security	243	general_concert_after_covid	people	die	ambulance	security
	72	general_concert_pre_covid	die	people	rip	pass
	127	vr_concert	die	people	concert	lose

Appendix -C (continued)

Topic	Frequency	Class	Term 1	Term 2	Term 3	Term 4
10_performance_live_amazing_best	171	general_concert_after_covid	performance	live	folder	amazing
	219	general_concert_pre_covid	performance	live	amazing	gnaw
	21	vr_concert	performance	papua	engine	sensational
38_legend_die_legends_rip	17	general_concert_after_covid	legend	awn	rash	ross
	96	general_concert_pre_covid	legend	rip	die	legends
	33	vr_concert	legend	legends	die	rip