applied sciences

MDPI

Article

Developing the NLP-QFD Model to Discover Key Success Factors of Short Videos on Social Media

Hsin-Cheng Wu [1], Wu-Der Jeng [2], Long-Sheng Chen [1,*] and Cheng-Chin Ho [1]

[1] Department of Information Management, Chaoyang University of Technology, Taichung 413310, Taiwan; ison@cyut.edu.tw (H.-C.W.); s11214609@gm.cyut.edu.tw (C.-C.H.)
[2] Department of Industrial Engineering and Management, Minghsin University of Science and Technology, Hsinchu 304001, Taiwan; jwd@must.edu.tw
* Correspondence: lschen@cyut.edu.tw

Abstract: In the transition from television to mobile devices, short videos have emerged as the primary content format, possessing tremendous potential in various fields such as marketing, promotion, education, advertising, and so on. However, from the available literature, there is a lack of studies investigating the elements necessary for the success of short videos, specifically regarding what factors need to be considered during production to increase viewership. Therefore, this study proposed the NLP-QFD model, integrating Natural Language Processing (NLP), Latent Dirichlet Allocation (LDA), and Quality Function Deployment (QFD) methods. Real short videos from mainstream Western media (CNN) and regional media (Middle East Eye) will be employed as case studies. In addition to analyzing the content of short videos and audiences' reviews, we will utilize the NLP-QFD model to identify the key success factors (KSFs) of short videos, providing guidance for future short video creators, especially for small-scale businesses, to produce successful short videos and expand their influence through social media. The results indicate that the success factors for short videos include the movie title, promotion, reviews, and social media. For large enterprises, endorsements by famous individuals are crucial, while music and shooting are key elements for the success of short videos for small businesses.

Keywords: short videos; key success factors; Quality Function Deployment; Natural Language Processing; social media reviews

Citation: Wu, H.-C.; Jeng, W.-D.; Chen, L.-S.; Ho, C.-C. Developing the NLP-QFD Model to Discover Key Success Factors of Short Videos on Social Media. *Appl. Sci.* **2024**, *14*, 4870. https://doi.org/10.3390/app14114870

Academic Editors: Reza Shahbazian and Irina Trubitsyna

Received: 9 April 2024
Revised: 3 June 2024
Accepted: 3 June 2024
Published: 4 June 2024

1. Introduction

In this digital age, short videos have become one of the main ways for people to express their opinions, share their insights, and attract attention [1]. This is especially true with the increasing popularity and influence of social media. In China, the number of users of short videos has exceeded 1 billion [2]. Recently, short video and audio platforms such as YouTube Shorts and TikTok have become important channels for the public to form opinions and communicate their viewpoints [3]. Due to the global popularization of short video applications, short videos have become an important topic.

In the transition from television to mobile devices, short-term videos have emerged as the primary content format, possessing tremendous potential in various fields [3]. Consequently, research on short videos has become one of the hot topics. Yuan and Wang [2] analyzed over 2000 articles and found that topics such as using short videos for marketing and their impact on education are currently popular. There is also a considerable amount of research focusing on the influence of short videos on stimulating online shopping and travel motivations [4], predicting the popularity of short videos [3,5], and advertising placement in short videos [6]. Therefore, it is evident that research related to short videos has become a trending topic. However, from the available literature, there is a lack of studies investigating the elements necessary for the success of short videos, specifically regarding what factors need to be considered during production to increase viewership.

Furthermore, research on how to create successful movies is also quite popular, as movie investors need to ensure significant returns on investment. Therefore, the topic of generating high box office revenue has become crucial, attracting many scholars to delve into it. For instance, Wang et al. [7] used big data to predict movie box office income, while Verma et al. [8] explored the elements, such as actors, directors, release dates, movie types, script quality, and movie ratings, necessary for a successful movie. Cizmeci et al. [9] found that social media marketing is crucial for a movie's success. Bae and Kim [10] argued that for a movie with inadequate promotion, the naming of the movie title can influence its box office performance. Jang et al. [11] conducted research on global video-on-demand (VOD) and found that popular original soundtracks (OSTs) have a significant impact on movie downloads.

Despite recent discussions on factors contributing to movie success, there is a lack of relevant research on the success factors for emerging short video platforms. Therefore, this study will consolidate these movie factors to serve as a candidate set of key success factors for short video platforms. Subsequently, this study proposed the NLP-QFD model, integrating Natural Language Processing (NLP), Latent Dirichlet Allocation (LDA), and Quality Function Deployment (QFD) methods. Short news videos from mainstream Western media (CNN) and regional media (Middle East Eye) will be employed as case studies. The collected data contain the video content and audience text reviews. We will use NLP and LDA methods to analyze the text of the video content and the reviews from social media. For comparing the differences in the content of short videos and the differences in audience perspectives after viewing, audio data will be transformed into textual data. In addition to analyzing the content of short videos and audience feedback, we will utilize the NLP-QFD model to identify the key success factors (KSFs) of short videos, providing guidance for future short video creators, especially for small-scale businesses, to produce successful short videos and expand their influence through social media.

To sum up, based on the available literature, there have been no previous studies focusing on the key success factors for short videos. Therefore, this study contributes by

(1) introducing the NLP-QFD method for identifying the key factors in short videos. This is the first time AI and NLP methods have been utilized to confirm key factors in short videos. The combination of NLP and QFD is also introduced for the first time, with results proving the effectiveness of the proposed method.

(2) By using real-life cases, it was confirmed that the key success factors for short videos include the movie title, promotion, reviews, and social media. Thus, creators of short videos need to focus extensively on these elements to ensure the effectiveness of their videos.

(3) It was discovered that the key success factors for producing short videos differ between small and large organizations. For large organizations, endorsements from famous individuals are crucial, as these organizations typically have the resources and credibility to secure endorsements from authoritative figures, strengthening the credibility and authority of their videos. In contrast, music and shooting are key elements for success in creating short videos for small organizations. By using emotional background music, impactful or sorrowful news soundscapes, and first-person shooting techniques, small organizations can immerse viewers in the experience and significantly enhance viewers' compassion and empathy, eliciting more resonance.

The first part of this article is the introduction, which explains the importance of the key success factors for short videos, the research background, motivation, and contributions. This is followed by a review of the relevant literature. Section 3 introduces the implementation steps of the proposed NLP-QFD model. Section 4 conducts experiments. Section 5 compares and discusses the key success factors of short videos in major mainstream media and regional media. Finally, the conclusion and suggestions for future research are presented in Section 6.

2. Related Works

2.1. Short Videos on Social Media

In recent years, short videos have gained immense popularity through social media, demonstrating their power in entertainment, education, and policy dissemination. More and more studies are focusing on the impact of platforms such as TikTok, YouTube Shorts, and Instagram Reels on human society. For example, Munoz et al. [12] evaluated the reliability of social media platforms YouTube and TikTok as sources of medical information on Dissociative Identity Disorder (DID). More than half of the respondents considered YouTube videos to be useful. Yuan and Wang [2] analyzed the content of over 2000 representative research papers on Chinese short videos published between 2012 and 2022. Their findings indicate that issues such as the marketing of short informative videos, standardized management of short video platforms, and the impact of these videos on university education suggest that short videos are likely to become a popular topic for future academic research.

In addition, Carpenter et al. [13] found that despite TikTok being one of the most popular social media platforms globally, educators have limited concerns about its usage. Their research revealed that participants were more inclined to engage with the platform for personal entertainment rather than professional reasons; however, they still found content that influenced their professional knowledge and practice. Alcántara-Pilar et al. [14] explored the factors influencing the credibility and trustworthiness of Key Opinion Leaders (KOLs) in TikTok marketing campaigns, as well as their subsequent impact on customer loyalty, purchase intentions, and recommendation behavior. Shoukat et al. [15] investigated the influence of internet influencers through TikTok on followers in the food and travel domains, finding that memorable local food experiences and travel influencer endorsements significantly positively affected revisit intentions.

Furthermore, Fang et al. [4] explored the factors inspiring travel through travel short videos, finding that hosts, destinations, and video design positively influence travel intentions. Cho et al. [3] developed an attention-based multimodal short-term video popularity prediction model to evaluate the popularity of short videos. Lu et al. [5] established a framework for simulating multimodal data in short videos, utilizing deep learning and text mining methods to consider likes, shares, and comments as response variables of short videos. Yin et al. [6] investigated advertising placement in short videos, exploring how to capture users' attention by triggering deferred completion desires to reduce users' defensive judgments of ads and stimulate potential passive demand.

From the above, it can be observed that influencers disseminating short-form videos indeed have an impact on their followers. In conclusion, research related to short videos has emerged as one of the latest research topics. However, there is a lack of studies understanding the elements needed for successful short videos during production to increase viewership. Therefore, this study aims to address this research gap.

2.2. Movie Success Factors

Due to the significant investment involved in filmmaking, investors must predict box office revenues in advance to assess the investment and promotional efforts for a film, ensuring a return on investment. Consequently, scholars have conducted research on predicting movie box office revenues to identify key factors influencing movie success. For example, Wang et al. [7] utilized big data to forecast movie box office revenue, considering factors such as screenwriting, casting, and shooting during the production stage, and promotion and scheduling during the distribution stage. Verma et al. [8] suggested that actors, directors, release dates, movie types, script quality, and ratings all impact a movie's success. Cizmeci et al. [9] found that social media significantly affects traditional movie marketing, leading movie studios to invest in social media advertising to increase box office revenue.

Kim et al. [16] explored additional factors influencing movie sales and revenue. They found that online reviews, movie genres, ratings, and the number of countries where a movie is released positively impact the number of days a movie is screened, which is considered one of the indicators of movie success. Their findings provide valuable insights for South Korean movie distributors when considering importing foreign films, including genres, expected ratings, and other characteristics.

Furthermore, Bae and Kim [10] suggested that for movies with insufficient promotion, apart from promoting through pre-release media exposure, an information-rich movie title positively affects box office revenue. Kim and Kim [17] studied the impact of theaters and post-theaters on movie success in the South Korean video-on-demand (VOD) market. Their main findings indicate that higher box office records and shorter retention periods are significant. The importance of box office performance on online performance can be explained by quality signals, promotional activities, or "me too" behavior. Jang et al. [11] conducted research on global video-on-demand (VOD) and found that movies suitable for all age groups, sequels, movies with fan bases, and movies with popular soundtracks (OSTs) are more likely to achieve higher sales through the download-to-own (DTO) model. Chen et al. [18] also explored important factors affecting the effectiveness of crowdfunding for movies, including casting and social media advocacy.

To sum up, although there have been discussions on factors contributing to movie success, movie crowdfunding projects, and video-on-demand in recent years, there is a lack of research on success factors for emerging short video platforms. Therefore, this study will consolidate these movie factors as a candidate set of key success factors for short video platforms. The NLP-QFD model will be proposed to identify the key success factors of short videos.

2.3. NLP

Natural Language Processing (NLP) is one of the subfields of artificial intelligence, which automatically represents and analyzes human language [19]. NLP is extensively used in analyzing user posts on social networks. This is because many individuals tend to express their true voices and genuine psychological states on social media to seek emotional comfort and recognition. Therefore, some studies focus on detecting depressive content early using NLP on user posts on social media platforms, which is an important research area [20,21]. For instance, Krishnamurti et al. [22] utilized NLP techniques and features from other patient-reported data as indicators of depression risk to detect depressive symptoms during pregnancy. Bhandarkar et al. [23] developed an NLP-based artificial intelligence model to predict suicide-related events within 30 days based on textual messages from patients.

Additionally, NLP is also used to analyze the content of user posts on social media. For example, Maypou et al. [24] used NLP techniques to analyze the implied advertising elements in Yelp reviews. Maypou et al. [25] also employed NLP techniques to delve into the rapid dissemination of fake news on social media. NLP is often combined with machine learning methods [26], such as in the study by Chang et al. [27], who used feature selection methods and NLP techniques to analyze the semantics of social media posts. Chen et al. [28] utilized NLP techniques and text mining methods to predict the viewership of live broadcasts based on user posts on social media. Chang et al. [29] employed NLP to analyze user comments from travel websites on social media, investigating factors contributing to customers' decisions not to revisit.

Consequently, following this trend of successful NLP applications, this study also employs NLP techniques to process textual comments from social media users on media short videos to discover different perspectives in our proposed NLP-QFD model.

2.4. LDA

In recent years, LDA has also been successfully applied to quickly identify important concepts and themes from large text data. For example, Li et al. [30] designed a model that combines Text Convolutional Neural Networks (TextCNNs) and Bidirectional Long Short-Term Memory (BiLSTM) to identify key information in COVID-19 data. Zou et al. [31] used LDA to extract 26 main research topics from 13,976 abstracts of Chinese policy research papers in the Web of Science (WOS), aiming to identify research topics on China's energy transition policy and predict future research trends. Yu et al. [32] used LDA to extract ten latent key scientific topics from a dataset containing 33,957 articles, providing a comprehensive overview of fuzzy research over several decades. Wahid et al. [33] argued that social media text data can be utilized for disaster management. However, in reality, there is a scarcity of disaster text data, and the manually labeled data available are highly imbalanced in the context of disasters. Therefore, they proposed the Topic2labels (T2L) framework, which provides an automated way of labeling data through the LDA topic modeling approach and utilizes BERT (Bidirectional Encoder Representations from Transformers) embeddings to construct feature vectors for contextual data classification.

From the above literature, it can be shown that LDA has been widely successful in text processing, summarizing large amounts of text data into a few important topics quickly for human understanding. Therefore, our NLP-QFD model also integrates LDA to rapidly summarize the topics within a large number of short videos.

2.5. QFD

Quality Function Deployment (QFD), also known as the House of Quality (HoQ), is a method used to translate the Voice of the Customer into product design specifications. Traditionally, QFD has been a tool for converting customer requirements into technical requirements [24]. In recent studies, it has been used to map the relationship between two key aspects to identify important factors. For example, Mayopu et al. [24] utilized text mining techniques and QFD to extract customer needs from text comments in social media using Latent Semantic Analysis (LSA) and transform them into advertising elements to determine the implicit advertising elements in social media comments. On the other hand, Chen et al. [34] used the contradiction matrix in QFD to identify conflicts between requirements for multiplayer online game products and applied the TRIZ creative problem-solving method to propose innovative game features. Lin et al. [35] used QFD to help identify innovative product functions for RFID technology in their work.

Based on the literature discussed above, it is evident that QFD has a long history of successful applications. Therefore, in our NLP-QFD model, after using NLP and LDA to identify a few important topics covered in a large number of short videos, we will also employ QFD to establish connections between these important concepts and the key success factors of short videos in order to determine the critical success factors of short videos.

3. Methodology

This study proposed an NLP-QFD model to identify the key success factors (KSFs) of short videos. The detailed steps included in this model could be divided into 7 steps. An implemental flowchart has been provided in Figure 1. The concise steps are provided below.

Step 1: Data Collection

This study focuses on short videos, including their contents and reviews. Specifically, it concentrates on YouTube Shorts, collecting video content, descriptions, and audience comments from platforms such as CNN-YouTube and Middle East Eye-YouTube. The YouTube Data API v3 will be used as a web crawler tool to extract comments, video content, descriptions, social media links, audience feedback, and other relevant factors. YouTube Shorts is chosen as the primary focus due to its widespread popularity, and CNN-YouTube and Middle East Eye-YouTube are selected as data sources to analyze events from both official media and user-generated content perspectives through audience comments.

Step 2. Transform audio data into text data

In order to compare the video content to social media users' comments, the videos include audiovisual elements. Therefore, based on audio, the collected video content will be transcribed into text format using Just Recap (https://reccap.it/ accessed on 1 March 2024) for further analysis and comparison.

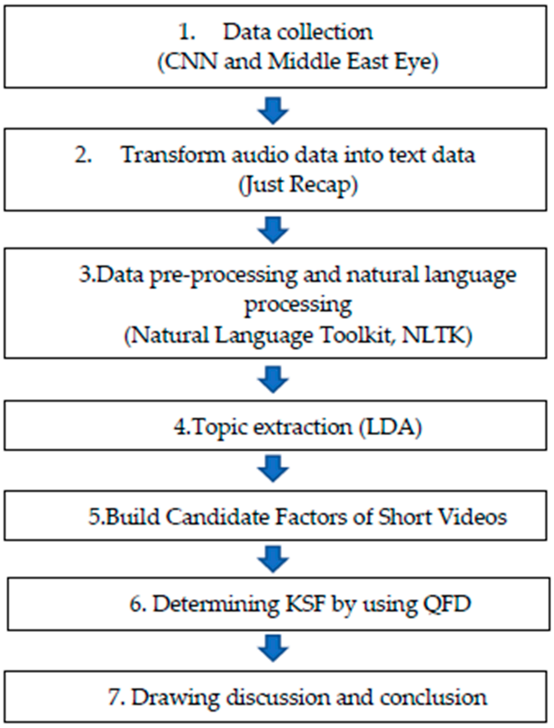


Figure 1. Implemental procedure of this study.

Step 3. Data pre-processing and natural language processing

We used Python to pre-process the collected text data. The pre-processing phase includes several steps, such as tokenization and lemmatization, before obtaining the TDM for LDA analysis. Natural Language Processing (NLP) takes into account intriguing text mining applications, and this method is qualified to extract pre-existing knowledge from the text. The complex sentences that occasionally appear in social media user-generated content with the intention of objective communication can be significantly extracted using NLP. The implementation process can be summarized as follows [19,36].

Step 3.1: Tokenization

The Python Natural Language Toolkit (NLTK) has been used for text tokenization. "Uni-gram" has been used to segment sentences.

Step 3.2: Data cleaning

In this step, we remove stop words such as "and" and "or", non-English words such as those in Arabic or Hebrew, and some meaningless icons to clean collected data.

Step 3.3: Lemmatization

The aim of this step is to reduce complex forms of a single word to their most basic form, such as "wrote" and "written" to "write".

Step 3.4: Calculate term frequency

A word frequency count has been performed and the terms with a frequency of less than 10 will be removed.

Step 3.5: Construct Term-Document Matrix (TDM)

In this step, we create a Term-Document Matrix (TDM) using the TF-IDF (term frequency-inverse document frequency) weights shown in Equation (1).

$$TF - IDF = TF(t_i, d_i) \times \log\left(\frac{N}{N(t_i)}\right) \tag{1}$$

where t_i means the ith term; d_j represents the jth document; N is the total number of all documents; N (t_i) denotes the number of documents which contain t_i features.

Step 4: Topic Extraction

Latent Dirichlet Allocation (LDA) is a machine learning technique used for topic modeling and is capable of discovering the thematic structure within a collection of texts. In this study, LDA will aid in exploring the latent themes and patterns within video content, descriptions, and audience comments. The steps for executing LDA include text preprocessing, setting LDA model parameters, fitting the LDA model, and interpreting and analyzing the results to understand the thematic structure and underlying patterns within the text data.

In this study, the coherence score has been employed to determine the number of selected topics in the LDA model. Next, the terms with high loadings will be considered as keywords in the selected topics. Finally, based on the selected keywords in each topic, the extracted topics could be named.

Step 5: Build Candidate Factors of Short Videos

As there is currently no specialized literature addressing the key success factors of short videos, this study searched for success factors in movies, movie crowdfunding projects, and movies on video-on-demand platforms from the limited relevant literature to serve as a candidate factor set of short videos.

Since there is currently no literature specifically addressing the key success factors of short videos, this study searched for success factors in movies, crowdfunding for films, and movies on video-on-demand platforms from the limited relevant literature. These were considered as candidate factors for the key success elements of short videos, and their definitions in the context of short videos are presented in Table 1.

Table 1. Candidate factors of short movies.

Notation	Factors	Definitions	Supports
S1	Famous guys	The famous individuals or officers in short videos.	[7,8,18]
S2	Social Media	Utilizing social media platforms to enhance the dissemination power of short videos.	[7,9,11,17]
S3	Shooting	Referring to the cinematography techniques and methods used in filming. It can make the audience feel like they are there.	[7,18]
S4	Storyline	The storyline of a short movie highly determines its performance.	[7,8,18]
S5	Reviews	The reviews or comments from those who have already watched the video can influence the viewing intention of those who have not yet watched it.	[16,17]
S6	Movie title	The title of a short movie. An informative movie title has a positive impact on the amount of views.	[10]
S7	Promotion	In this study, it refers to the name of the media being mentioned. It can enhance the credibility of short news videos.	[7,17,18]
S8	Music	In this study, it refers to emotionally gripping music or real-world background voices.	[11]

Step 6: Determining KSFs by using QFD

Next, QFD has been used to find the relationship between short video factors and the extracted topics from LDA. A team of domain experts has been constructed to determine the final scores of relationships following the procedure.

(1). Identify domain experts

Five experts who are knowledgeable about short videos and social media will be included in the team.

(2). Define scoring criteria

Next, clear scoring criteria which outline how the experts should assign scores to each relationship within the matrix of QFD have been developed. For instance, "9", "3", and "1" represent a "strong", "moderate", and "weak" positive relationship, respectively.

(3). Independent scoring and collect scores

In this step, each expert independently evaluates and scores the relationships within the matrix according to the established criteria. Then, the scores from each expert are gathered.

(4). Aggregation of Scores

The scores are aggregated from all the experts for each cell in the matrix.

(5). Analysis, discussion, and determining final scores

In this step, all experts will analyze the aggregated scores to reach an agreement or disagreement among the experts. Finally, final scores will be determined after full discussion.

(6) Determining the KSFs of short video

Finally, based on the scores of short video factors, KSFs could be determined.

Step 7: Discussion and Drawing Conclusions

Discussion and conclusions will be conducted based on the identified topics extracted from the analysis.

4. Results

In this section, we will delve into the key findings and analyses derived from video content and audience comments and discover KSFs by using our NLP-QFD model.

4.1. Used Case and Data Collection

On 7 October 2023, Palestinian Hamas launched an offensive against Israel, and Israel immediately launched a comprehensive counterattack, starting another Israeli–Palestinian conflict. The war continues to this day. During this period, we particularly noticed that most of the media used social networks to convey different views on the Israeli–Palestinian conflict between the West and the Middle East.

In the early days of the conflict, Western media such as CNN dominated global public opinion. However, we have observed that a relatively small number of weak media in the Middle East have systematically produced short videos, expressed their opinions on social media, and used real and vivid videos to counter mainstream media reports through voice platforms such as TikTok and YouTube. They won partial recognition [37] and successfully conveyed the voices of local disadvantaged groups to the world.

Generally speaking, traditional mainstream media and emerging self-media often have different views and positions on such conflict reports, which has attracted widespread attention [36]. This situation prompts us to think about whether there are significant differences in the treatment of related videos by self-media and state media on platforms such as YouTube Shorts, especially on sensitive topics such as the Israeli–Palestinian conflict.

On emerging audio and video platforms such as YouTube Shorts, it is unclear whether the different viewpoints conveyed by the respective reported videos have an impact on the audience, which is also the motivation of this study. We will conduct an in-depth study of the way self-media and state media handle content related to the Israeli and Palestinian conflicts on YouTube Shorts and explore the appeal and impact of this treatment on audiences.

Therefore, this study takes YouTube Shorts related to the conflict between Israel and Palestine as an example to compare videos related to the conflict between Israel and Palestine between self-media and official media on social media platforms to understand whether there is a significant difference in attracting the audience's attention.

Finally, we collected the top 60 most-viewed short videos from the YouTube channels of Middle East Eye (Figure 2) and CNN (Figure 3), respectively, during the first three months before the October–December period of 2023, which encompasses the prelude to the Israel–Palestine conflict.

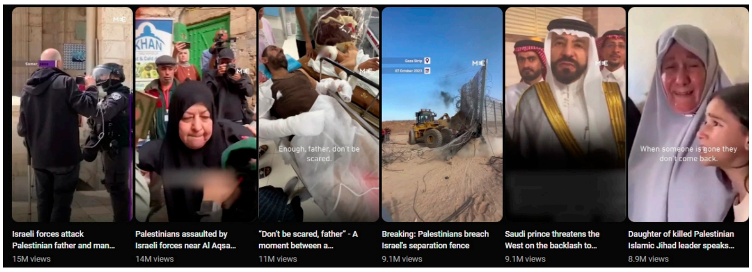


Figure 2. Some examples of short videos from Middle East Eye YouTube.

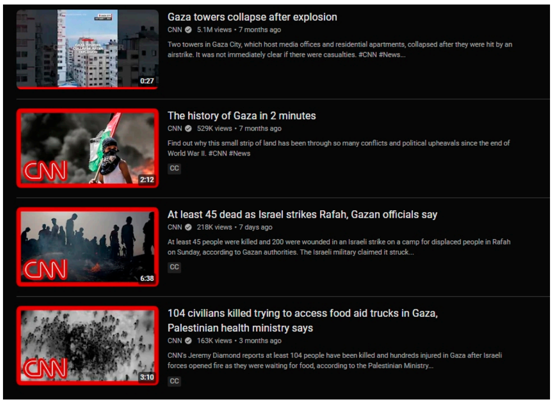


Figure 3. Some examples of short videos from CNN YouTube.

A total of 120 videos were collected, covering various topics and events related to the conflict. Using the YouTube Data API v3 as our web crawler tool, we obtained data such as video content, descriptions, and viewer comments from these videos. Additionally, we utilized "JustRecap" (https://reccap.it/try accessed on 1 March 2024), a natural language processing (NLP) tool, to convert the audio-visual content of the short videos into textual data for comparison with viewer comments.

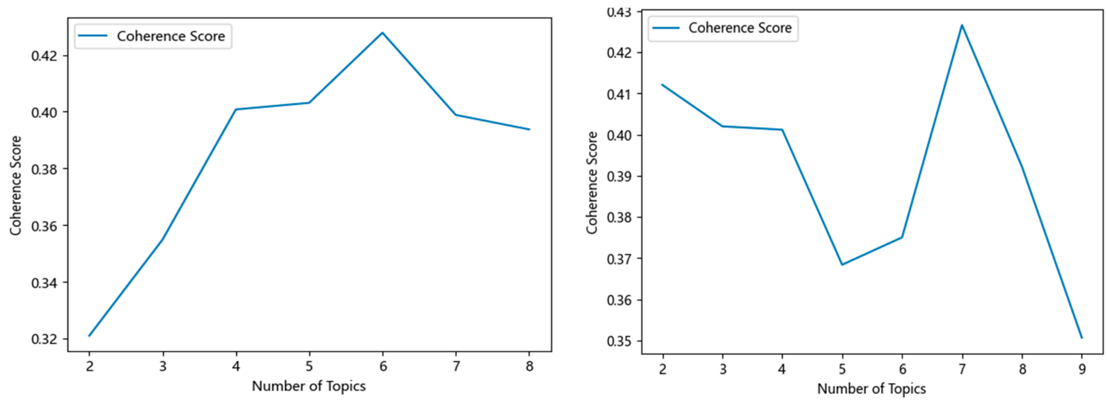
In the viewer comments section, we collected a total of 3874 comments. After data cleaning, 2006 comments were retained, with 698 from CNN-YouTube and 1308 from Middle East Eye-YouTube. These comments were then processed through natural language processing to create term-document matrices.

4.2. Results of LDA

4.2.1. Authentic Voices behind News Short Videos

In ensuring the determination of the optimal number of topics, we employed the coherence score as a consistent indicator. In natural language processing, the coherence score of an LDA topic model serves as a metric to evaluate the coherence and consistency of the topics generated by the model. The coherence score measures the relevance among different words within the same topic, which ideally should co-occur within a topic. A higher coherence score indicates that the words within the topic are more correlated and coherent, whereas a lower score suggests that the words within the topic are more disparate and unrelated. Therefore, by calculating the coherence score, we can assess the quality of the LDA topic model and compare the performance of the model across different numbers of topics.

Figures 4a and 4b, respectively, depict the Coherence scores of the CNN and Middle East Eye cases under different numbers of topics. From the graphs, we observe that the highest Coherence scores are achieved when the number of topics is 6 and 7, indicating that, in terms of audience textual comments, the optimal number of topics for both cases is 6 and 7, respectively. Figures 5 and 6 present implicit Dirichlet distributions of audience comments, enabling us to label these topics accordingly.



(**a**) (**b**)

Figure 4. Coherence score in audience's reviews. (**a**) CNN case; (**b**) Middle East Eye.

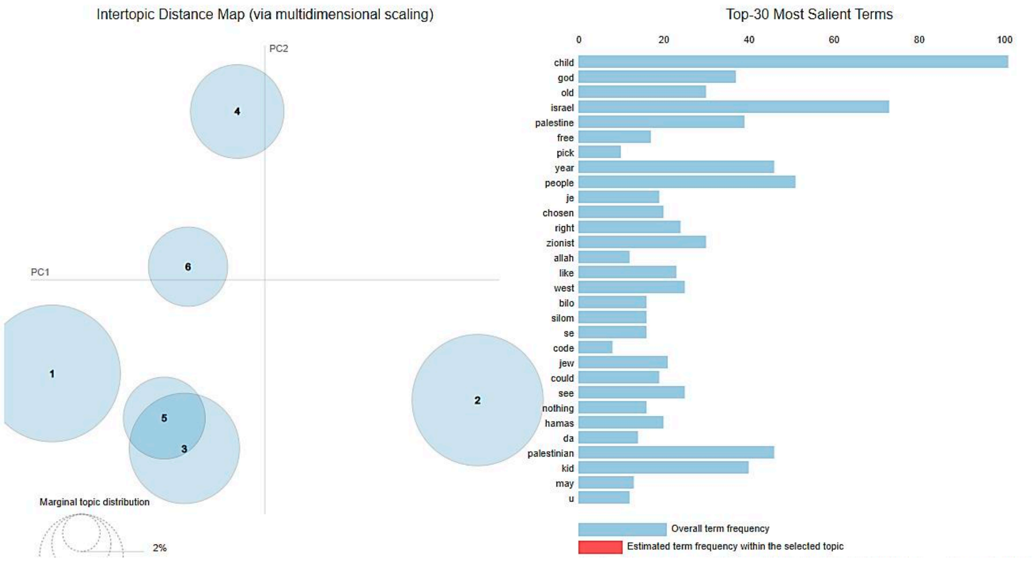


Figure 5. The Dirichlet distribution of audience comments (CNN-YouTube).

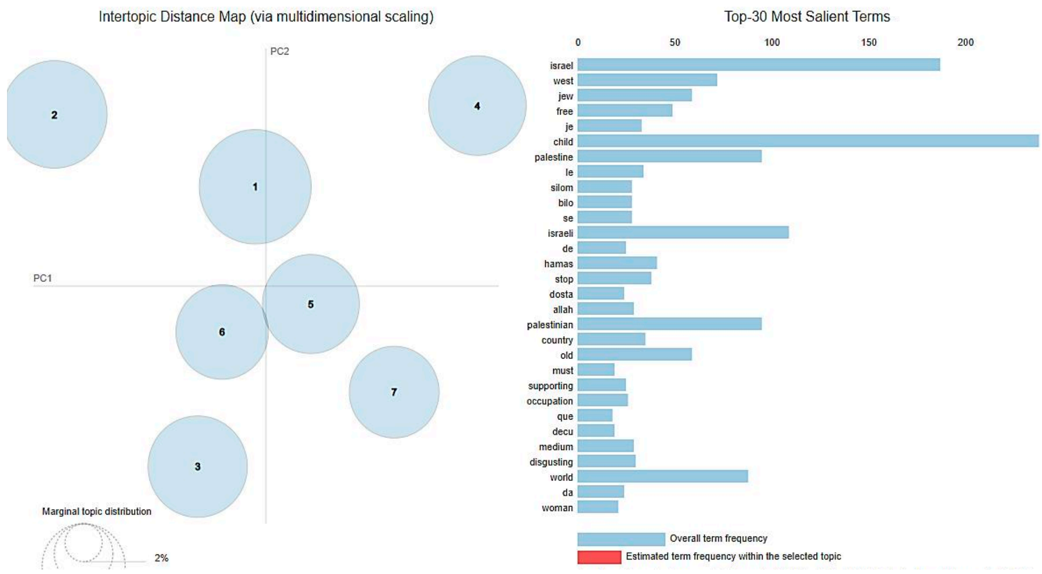


Figure 6. The Dirichlet distribution of audience comments (Middle East Eye-YouTube).

In Figures 5 and 6, the left-hand side is a Matrix Data Analysis Diagram, which is a visual representation used in data analysis to display relationships between different variables within a dataset. It typically presents data in a tabular format. This type of diagram can be particularly useful for identifying patterns, trends, or dependencies in large datasets and for conducting various types of statistical analyses, such as correlation analysis or factor analysis. In this study, we can use the Matrix Data Analysis Diagram to understand the relationships among extracted concepts. In Figure 5, we can see that topics #3 and #5 have overlaps when the selected seven topics are relatively independent.

In addition, the right-hand side of Figures 5 and 6 summarizes the top 30 most salient terms. In the audience comments for CNN (Figure 5), we can observe that besides place names such as Israel and Palestine, the most frequently occurring words are Child, Kid, People, God, etc. This indicates a concern for the local people and children amidst the conflict in Palestine. In Figure 6, for Middle East Eye, the most frequent words in the audience comments include Child, as well as west, world, stop, and old, suggesting voices primarily from those affected by the war.

Next, the extracted topics should be named. Table 2 lists representative words in six selected topics from the CNN short videos. These six topics are named as follows.

Table 2. Extracted topics from social media users' comments (CNN).

Topic #1		Topic #2		Topic #3		Topic #4		Topic #5		Topic #6	
Terms	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**
child	0.022	israeli	0.022	child	0.033	god	0.02	israel	0.026	israel	0.031
israeli	0.017	child	0.017	palestine	0.022	je	0.017	child	0.021	kid	0.025
kid	0.016	israel	0.017	year	0.015	silom	0.015	old	0.015	child	0.015
palestinian	0.012	palestinian	0.017	free	0.015	bilo	0.015	could	0.014	stop	0.014
zionist	0.011	human	0.012	israel	0.013	se	0.015	leader	0.014	israeli	0.012
people	0.011	call	0.012	right	0.01	people	0.014	world	0.012	palestinian	0.012
world	0.01	animal	0.012	stop	0.01	chosen	0.013	one	0.011	year	0.011
israel	0.009	de	0.011	old	0.009	immoral	0.013	shame	0.011	please	0.011
one	0.008	people	0.011	kid	0.009	dosta	0.012	yr	0.01	allah	0.011
see	0.007	year	0.009	west	0.009	da	0.01	boy	0.008	west	0.011
year	0.007	right	0.009	never	0.009	decu	0.01	treat	0.008	zionist	0.010
heart	0.007	like	0.008	nothing	0.009	israel	0.009	lie	0.007	people	0.010
generation	0.007	world	0.008	going	0.009	barbaric	0.008	coward	0.007	old	0.009
must	0.007	know	0.008	pick	0.009	see	0.008	whole	0.007	humanity	0.008
crime	0.007	jew	0.008	innocent	0.008	state	0.007	wish	0.007	peace	0.008
state	0.006	terrorist	0.007	need	0.008	zlocine	0.007	way	0.007	need	0.008
cry	0.006	thing	0.007	palestinian	0.008	zla	0.007	become	0.007	watch	0.008
time	0.006	south	0.007	jew	0.007	genocida	0.007	dare	0.007	kidnapper	0.008
real	0.006	speak	0.007	nazi	0.007	masakra	0.007	innocent	0.007	generation	0.008
innocent	0.006	also	0.007	stone	0.007	allah	0.007	israeli	0.007	palestine	0.008
kidnapper	0.005	native	0.007	crazy	0.007	zionist	0.007	arrested	0.007	may	0.008
abuse	0.005	africa	0.007	arrest	0.007	happened	0.007	today	0.007	future	0.008
code	0.005	boy	0.007	hamas	0.007	still	0.007	hamas	0.006	crime	0.008
humanity	0.005	may	0.007	people	0.007	human	0.007	know	0.006	state	0.007
palestine	0.005	west	0.002	name	0.006	may	0.007	crime	0.006	government	0.007

Topic #1: History of Conflict and Accusations in Israel and Palestine

This topic represents keywords primarily related to Israel, Palestine, children, Jewish nationalists, crimes, state, innocence, kidnappers, etc. It focuses on the historical conflict in Israel and Palestine and subsequent accusations against Israeli measures of segregation and Palestinian kidnappers.

Topic #2: Gaza Blockade and Aid from Southern African Nations

This topic includes keywords such as humanity, animals, rights, terrorists, southern, Africa, etc. It mainly discusses the basic human rights in Palestinian and Israeli-occupied territories, including aid from southern African nations.

Topic #3: Israeli Incursion and Hamas Counteraction

Keywords in this topic include freedom, rights, stop, West, ongoing, Nazi, stone, Hamas, arrest, etc. It primarily discusses Israeli incursions and both support for and opposition to Hamas' actions, asserting the rights of Gaza residents and the need to uphold their freedom.

Topic #4: Accusations of Genocide

Keywords in this topic include God, immoral, barbaric, crimes, evil, genocide, massacre, and Allah, focusing on various accusations of genocide against Israel.

Topic #5: Critique of Media Bias

Representative keywords are leader, world, shame, lies, coward, arrested, and crimes, focusing on accusations against Western media for biased reporting on the Middle East.

Topic #6: Call for an End to War

Keywords in this topic include children, stop, please, Allah, humanity, and peace, focusing on pleas for an end to war and the pursuit of peace.

Table 3 summarizes the seven topics from short video audience comments of Middle East Eye. These seven topics are named as follows.

Table 3. Extracted topics from social media users' comments (Middle East Eye).

Topic #1		Topic #2		Topic #3		Topic #4		Topic #5		Topic #6		Topic #7	
Terms	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**
palestine	0.050	israel	0.034	child	0.028	israeli	0.021	child	0.033	Israel	0.027	child	0.042
free	0.028	jew	0.017	year	0.020	west	0.021	know	0.015	Je	0.020	israel	0.022
please	0.021	israeli	0.016	israeli	0.016	child	0.020	israel	0.015	Bilo	0.017	human	0.017
stop	0.020	monster	0.014	old	0.015	world	0.017	people	0.015	Silom	0.017	world	0.015
child	0.018	animal	0.013	kid	0.015	palestinian	0.016	see	0.012	Se	0.017	innocent	0.013
israel	0.017	rule	0.012	hamas	0.012	one	0.015	palestinian	0.011	dosta	0.014	terrorist	0.012
kid	0.017	child	0.012	israel	0.012	year	0.013	country	0.010	Le	0.012	palestinian	0.012
innocent	0.014	kid	0.011	like	0.011	jew	0.012	year	0.010	supporting	0.011	israeli	0.011
right	0.013	regime	0.010	west	0.010	old	0.012	throwing	0.010	decu	0.011	people	0.010
world	0.012	time	0.009	terrorist	0.010	people	0.011	zionist	0.009	Da	0.011	criminal	0.009
going	0.011	world	0.009	palestinian	0.010	right	0.010	medium	0.009	disgusting	0.008	know	0.009
people	0.011	isreal	0.009	must	0.010	zionist	0.010	freedom	0.009	genocida	0.008	ameen	0.009
men	0.010	truth	0.009	beyond	0.010	israel	0.010	humanity	0.008	zla	0.008	kind	0.009
year	0.010	hitler	0.009	medium	0.009	de	0.009	well	0.007	masakra	0.008	kid	0.009
leader	0.008	south	0.009	police	0.009	state	0.009	leader	0.007	zlocine	0.008	drake	0.008
crazy	0.008	compared	0.009	know	0.009	never	0.008	anti	0.007	que	0.008	breaking	0.008
never	0.008	million	0.009	try	0.007	human	0.008	around	0.007	evil	0.007	grow	0.008
occupation	0.008	exposed	0.009	could	0.007	idf	0.007	tell	0.007	government	0.007	humanity	0.007
fighting	0.008	native	0.009	state	0.007	america	0.007	call	0.007	future	0.007	go	0.007
hammas	0.008	africa	0.009	said	0.007	nothing	0.007	victim	0.007	generation	0.007	fighter	0.007
iseail	0.008	state	0.008	jew	0.007	today	0.006	abuser	0.006	state	0.007	like	0.007
israil	0.008	like	0.008	crime	0.006	happen	0.006	horror	0.006	watch	0.006	may	0.007
nthat	0.008	founded	0.008	zionist	0.006	would	0.006	hostage	0.006	stand	0.006	rule	0.007
imposed	0.008	based	0.008	right	0.006	god	0.006	security	0.006	su	0.006	done	0.007
see	0.007	war	0.008	nazism	0.006	hamas	0.006	stone	0.006	israel	0.006	justice	0.007

#1 Palestinian Rights and Call for Ceasefire

This theme primarily features keywords such as freedom, please, stop, children, innocence, rights, world, leaders, etc. These comments emphasize the freedom and human rights of Palestinians, calling for Israel and world leaders to stop the war.

#2 Accusations of Israeli Rule and Injustice

Keywords include Jewish people, Israelis, monsters, animals, rule, children, regime, truth, and Hitler. These comments mainly accuse Israel of its war and governance measures.

#3 Western Media Coverage of Israel and Hamas

Keywords include children, Israelis, elderly, children, Hamas, Western, terrorists, Palestinians, beyond, media, and police. These comments discuss the coverage of Israel and Hamas by Western media.

#4 Call for Western Countries to Mediate

Keywords include Western, children, world, people, rights, Germany, and USA. These comments focus on human rights, especially for vulnerable groups such as children and the elderly, calling for Western intervention in the conflict between Israel and Hamas and for a ceasefire.

#5 Discussion on Israeli Military Entry into the Gaza Strip

Keywords include know, see, throwing, media, freedom, humanity, leaders, opposition, surrounding, tell, appeal, victims, abusers, terror, and hostages. These comments mainly discuss the Israeli military's entry into the Gaza Strip.

#6 Opposition to Genocide, Support for Palestinian Statehood

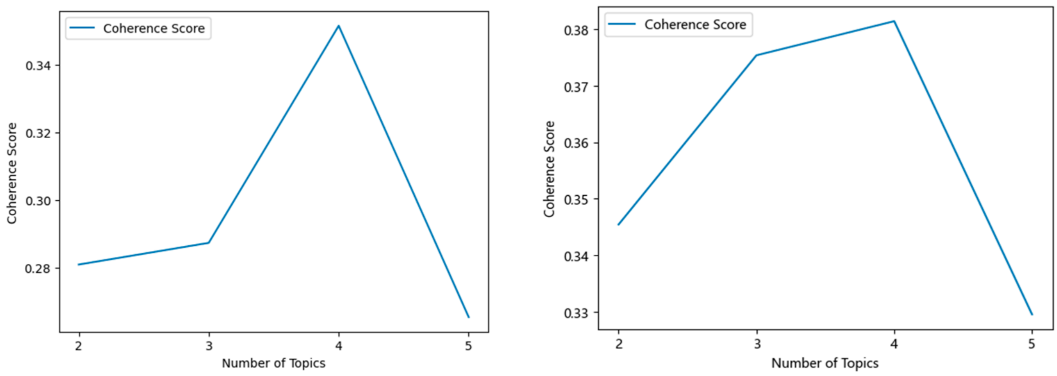
Keywords include stop, enough, support, disgusting, genocide, evil, massacre, crimes, evil, government, future, generation, and country. These comments express a desire to stop all violence and support the establishment of their own country for a better future.

#7 Condemnation of War, Hope for a Better Future

Keywords include world, innocent, terrorists, criminals, know, kindness, breakthrough, growth, humanity, progress, fighters, rule, and justice. They primarily condemn war and express hope for a better future.

4.2.2. Short Video Content Analysis

Following the LDA analysis of short audio-visual news reports, this study found that regardless of whether the reports came from CNN or Middle East Eye, the optimal number of topics is four, as indicated by the Coherence score in Figure 7.



(**a**) (**b**)

Figure 7. Coherence score in short video content. (**a**) CNN case; (**b**) Middle East Eye.

After determining the optimal number of topics, the analysis focused on CNN's reporting content, extracting four topics and their representative words as shown in Table 4. The names and representative words for the four topics are as follows:

#1 Terrorist Attacks

This topic primarily includes words such as Hamas, Gaza, Attack, Tunnel, War, Inside, Music, Hostage, Troop, etc. The reports mainly focus on Hamas attacks on Israeli events, such as music concerts, and the capture of Israeli hostages. It also mentions assistance from Lebanon Hezbollah.

#2 Western Student Anti-War Movement

This topic mainly includes words such as Student, Speech, Gaza, Impact, Free, Debate, Campus, Career, Anti War, College, etc. It focuses on debates against war initiated by students on Western university campuses and the responses of Western enterprises to student movements.

Table 4. Extracted topics from news short video content (CNN).

Topic #1		Topic #2		Topic #3		Topic #4	
Terms	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**	**Terms**	**Loadings**
hamas	0.034	hamas	0.031	israeli	0.025	Hamas	0.017
gaza	0.031	israel	0.027	gaza	0.023	Israeli	0.013
israel	0.025	student	0.021	israel	0.021	Israel	0.013
israeli	0.022	speech	0.017	conflict	0.011	violence	0.011
attack	0.015	gaza	0.014	family	0.011	Tension	0.010
tunnel	0.014	impact	0.011	situation	0.011	palestinian	0.010
war	0.012	free	0.011	military	0.009	Threat	0.008
inside	0.009	debate	0.011	palestinian	0.009	Jewish	0.008
military	0.008	israeli	0.011	border	0.007	War	0.008
music	0.007	campus	0.009	impact	0.007	university	0.008
hostage	0.007	career	0.009	minister	0.007	across	0.007
troop	0.007	war	0.008	prime	0.007	community	0.007
video	0.007	anti	0.008	individual	0.007	muslim	0.007
people	0.006	public	0.008	death	0.007	student	0.007
day	0.006	college	0.008	operation	0.006	Fear	0.006
summary	0.006	firm	0.008	tension	0.006	protest	0.006
show	0.006	offer	0.008	killed	0.006	World	0.006
effort	0.006	job	0.008	foreign	0.006	Gaza	0.006
netanyahu	0.006	attack	0.008	hostage	0.006	hezbollah	0.004
aid	0.006	law	0.008	rocket	0.006	lebanon	0.004
document	0.006	military	0.006	including	0.006	express	0.004
lebanon	0.006	conflict	0.006	humanitarian	0.006	leading	0.004
hezbollah	0.006	statement	0.006	netanyahu	0.006	Rally	0.004
content	0.006	semitic	0.006	aid	0.006	Call	0.004
festival	0.004	professor	0.006	attack	0.006	demonstration	0.004

#3 Israeli–Palestinian Military Conflict

This topic mainly includes words such as Conflict, Military, Border, Minister, Prime, Death, Operation, Tension, Rocket, Humanitarian, etc. It reports on the military and blockade actions taken by both Israel and Palestine after the Hamas attack, including hostage situations and appeals for humanitarian aid.

#4 Support for Gaza Civilian Demonstrations and Protests

This topic mainly includes words such as Violence, Tension, Threat, University, Community, Muslim, Student, Protest, Rally, Demonstration, etc. It primarily reports on various demonstrations and protests initiated by various communities, including university students and Muslims, to support civilians affected in the Gaza Strip.

Next is the analysis of the Middle East Eye's reporting content. It is well known that the Middle Eastern media's stance differs from mainstream Western media. Table 5 summarizes the extracted four topics and their representative terms. The names and key words of these four reporting topics are described as follows:

#1 Expressing US Support for Israeli Policies

This topic includes words such as Israel, Palestinian, action, weapons, express, US, protest, policy, Gaza, killing, humanitarian, etc. These reports mainly express the Middle Eastern perspective on US support for Israeli military actions and report casualties in the Gaza Strip, calling for humanitarian consideration and assistance to the Palestinian people.

#2 Bombing Hospitals and Reactions to Civilian Casualties in Gaza

This topic includes words such as children, hospitals, Yemen, hope, peace, safety, civilian, ceasefire, urging, moral, equality, loss, death, etc. The reports focus on Israeli military bombings of hospitals, resulting in casualties among children and civilians, as well as reactions from neighboring countries such as Yemen. They call for intervention for a ceasefire.

Table 5. Extracted topics from news short video content (Middle East Eye).

Topic #1		Topic #2		Topic #3		Topic #4	
Terms	Loadings	Terms	Loadings	Terms	Loadings	Terms	Loadings
israel	0.026	gaza	0.021	express	0.017	gaza	0.024
israeli	0.017	child	0.019	palestinian	0.015	israeli	0.017
palestinian	0.012	hospital	0.019	someone	0.010	palestinian	0.014
action	0.010	yemen	0.019	attack	0.010	journalist	0.013
transfer	0.009	israeli	0.014	girl	0.010	child	0.013
arm	0.009	people	0.012	people	0.010	u	0.013
express	0.009	palestinian	0.012	family	0.010	speaker	0.009
u	0.007	soldier	0.010	difficulty	0.010	american	0.009
protest	0.007	war	0.010	despite	0.010	destruction	0.009
policy	0.007	hope	0.010	determination	0.010	government	0.009
gaza	0.007	year	0.007	bombing	0.010	hospital	0.009
state	0.006	peace	0.007	living	0.008	home	0.007
simon	0.006	feeling	0.007	rubble	0.008	terrorist	0.007
military	0.006	safety	0.007	come	0.008	one	0.007
event	0.006	civilian	0.007	describes	0.008	hour	0.007
speaker	0.006	ceasefire	0.007	killed	0.008	displaced	0.006
conflict	0.006	call	0.007	emphasizes	0.008	survivor	0.006
old	0.005	clarity	0.007	one	0.008	five	0.006
year	0.005	moral	0.007	speaker	0.008	house	0.006
hostage	0.005	equal	0.007	mother	0.008	urging	0.006
killing	0.005	losing	0.005	loved	0.008	san	0.006
human	0.005	death	0.005	closer	0.008	disengagement	0.006
discussion	0.005	importance	0.005	loss	0.008	plan	0.006
invitation	0.005	emphasizes	0.005	plea	0.008	people	0.006
captive	0.026	conflict	0.005	israeli	0.008	inside	0.005

#3 Plight of People in Blockaded Areas

This topic includes words such as express, Palestinian, girl, people, family, difficulty, bombing, living, rubble, killed, mother, loss, plea, etc. These reports mainly convey the plight of affected people in blockaded areas, including the loss of life and property.

#4 Local Journalists Killed in Bombing

This topic includes words such as Gaza, journalist, children, US, destruction, government, hospitals, terrorists, displaced, survivors, urging, UN, disengagement plan, etc. These reports focus on local journalists killed in bombings and the bombings of hospitals, urging the US and the UN to plan the evacuation of civilians affected by the war in Gaza.

4.3. Determining Key Success Factors of Short Videos

After identifying the themes of short video reports using NLP and LDA, the next step is to pinpoint the key success factors of these short videos. According to Table 1 which defined the candidate elements of short videos, the expert panel reached a consensus decision and utilized a Matrix diagram to correlate the strength of relationships between the reporting themes and these candidate elements. The results are presented in Table 6.

After correlating the reporting topics with the factors of short videos, we can calculate scores based on the given relevance, with higher scores indicating a stronger correspondence between these short video factors and the reporting topics. To sum up, in the CNN case, the results indicate that the Key Success Factors (KSFs) for short videos, ranked by their scores from highest to lowest, are famous guys (S1), movie title (S6), promotion (S7), reviews (S5), and social media (S2). In the Middle Easy Eye case, the higher-scoring KSFs are social media (S2), movie title (S6), music (S8), reviews (S5), shooting (S3), and promotion (S7).

Table 6. The relationship between elements of movies and the extracted topics in short videos.

	Movie Elements **Topics of Short Videos**	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**
CNN	Terrorist Attacks	◎	○	○	○	△	◎	◎	△
	Western Student Anti-War Movement	◎	◎			○	◎	◎	
	Israeli–Palestinian Military Conflict	◎		△	◎	○	◎	◎	△
	Support for Gaza Civilian Demonstrations and Protests	◎	○			◎	◎	◎	△
	score	36	15	4	12	16	36	36	3
Middle East Eye	Expressing US Support for Israeli Policies	○	◎	○	△	◎	◎	○	◎
	Bombing Hospitals and Reactions to Civilian Casualties in Gaza	○	◎	◎	◎	◎	◎	○	◎
	Plight of People in Blockaded Areas	◎	◎	◎	◎	◎	◎	◎	◎
	Local Journalists Killed in Bombing	○	◎	○	○	○	◎	◎	◎
	score	18	36	24	22	30	36	24	36

Note: ◎, ○, △ represent that the relationship between two factors is "strong", "medium", and "weak". Their scores are 9 points, 3 points, and 1 point, respectively.

5. Discussion

In this section, we will compare the differences between the KSFs of short videos and the differences in audiences' reviews. First, we discuss the KSFs. In Table 7, we list the top three groups of high-scoring key success factors. Here is an explanation for these high-scoring key factors:

For CNN's short videos, we can observe that the highest-scoring factors are famous individuals, movie titles, and promotion. Because CNN is a major media outlet, its reports need to carry a certain authority, and many official entities are willing to convey messages to the world through CNN. Therefore, in CNN's reports, promotion (S7) and famous individuals (S1) are crucial factors. In addition, due to the changing habits of the audience, the attractiveness of the title (S6) often determines whether they will watch the news report. Thus, news media outlets such as CNN usually have professionals designing their titles. Therefore, famous individuals, movie titles, and promotion are considered the top three key success factors for CNN videos.

Additionally, two other important elements are reviews (S5) and social media (S2), although their scores are relatively much lower. Regarding reviews (S5), editors must actively and frequently engage with social media users to proactively generate buzz for short videos. Furthermore, editors also need to manage social media platforms (S2), such as utilizing Facebook updates, Instagram hashtags, hyperlinks, etc., to facilitate community dissemination.

For Middle East Eye's short videos, the top three important factors are social media (S2), movie title (S6), and music (S8). Compared to CNN, Middle East Eye is a relatively small local media outlet aiming to expand its audience, so it actively utilizes "hashtags" or hyperlinks on social medias such as Instagram and TikTok to disseminate short videos. This is the reason why social media has been determined as a key success factor. In addition, similarly to CNN, movie title is also considered an important factor. The last important factor is music, which uses real-life background sounds such as a mother crying, explosive sounds, or the wailing of someone who lost a loved one to make the short video report more emotionally gripping.

Table 7. The top high-scoring key success factors of short videos.

CNN				Middle East Eye			
No.	**Score**	**Factor**	**Suggestions**	**No.**	**Score**	**Factor**	**Suggestions**
S1	36	Famous guys	Employ famous individuals or officers in short videos.	S2	36	Social Media	To use hashtags or hyperlinks in social media to disseminate short videos
S6	36	Movie title	Crafting precise short video titles to attract viewers.	S6	36	Movie title	Crafting precise short video titles to attract viewers.
S7	36	Promotion	To mention the name of the media in short videos	S8	36	Music	To use emotionally gripping music or real-world background sounds.
S5	16	Reviews	The editors should engage more frequently with social media users.	S5	30	Reviews	The editors should engage more frequently with social media users.
S2	15	Social Media	To use hashtags or hyperlinks in social media to disseminate short videos.	S3	24	Shooting	To perform cinematography techniques in filming.
				S7	24	Promotion	To mention the name of the media in short videos.

In addition, "reviews" (S5) are also important, as the editors of Middle East Eye engage more frequently with social media users to focus the video's comments and shape its discourse. The last two factors are shooting (S3) and promotion (S7). Regarding the shooting factor, using a first-person shooting style allows viewers to empathize more with the perspectives of the interviewees through the short video report. Lastly, smaller media outlets such as Middle East Eye also need to mention brand names in their short videos to promote their media outlets and gain more sponsorships and advertising opportunities.

Next, Table 8 compares the differences in news short video content and in audience perceptions between CNN and Middle East Eye, as identified from textual comments. From this table, we can not only observe the differences in the focal reporting content and audience perspectives between CNN and Middle East Eye but also compare the disparities between the conveyed content and audience sentiments.

Firstly, let us delve into the news content. Overall, based on the analysis of video content, media news reports are structured and usually cover significant events, making the analysis results relatively easier to interpret. This is unlike audience comments, which are typically brief, unstructured, and often contain internet slang, requiring more time to decipher.

Looking at the themes identified from the video content of CNN and Middle East Eye, CNN adopts a Western perspective and targets a global audience, hence the need to provide historical context of the Israeli–Palestinian conflict, report on Western university students' anti-war movements, explain the progress of the Israeli–Palestinian military conflict, and depict the situation in the Gaza Strip. Essentially, CNN attempts to report the news from the standpoint of both conflicting parties, thereby conveying the plight of the affected population in the Gaza Strip.

Table 8. Summary of extracted topics from social media users' comments in CNN and Middle East Eye.

Data	Topic	CNN	Middle East Eye
Short Videos	#1	Terrorist Attacks	Expressing US Support for Israeli Policies
	#2	Western Student Anti-War Movement	Bombing Hospitals and Reactions to Civilian Casualties in Gaza
	#3	Israeli–Palestinian Military Conflict	Plight of People in Blockaded Areas
	#4	Support for Gaza Civilian Demonstrations and Protests	Local Journalists Killed in Bombing
Audience's Reviews	#1	History of Conflict and Accusations in Israel and Palestine	Palestinian Rights and Call for War Ceasefire
	#2	Gaza Blockade and Aid from Southern African Nations	Accusations of Israeli Rule and Injustice
	#3	Israeli Incursion and Hamas Counteraction	Western Media Coverage of Israel and Hamas
	#4	Accusations of Genocide	Call for Western Countries to Mediate
	#5	Critique of Media Bias	Discussion on Israeli Military Entry into Gaza Strip
	#6	Call for an End to War	Opposition to Genocide, Support for Palestinian Statehood
	#7	-	Condemnation of War, Hope for a Better Future

On the other hand, Middle East Eye reports news from a local standpoint. In addition to reporting on US support for Israeli policies, the focus is more on extensive coverage of bombings on hospitals and other locations, capturing the cries and pleas of affected civilians. This also includes the tragic deaths of local journalists due to the impact of explosions. We can observe some differences in the emphasis of reporting between the two sides.

Next, we compare the differences in the audience's voice. Many members of CNN's audience may not be well-informed about the history of the Israel–Palestine conflict, hence the first theme discusses the historical context of the conflict. There are also those who are familiar with the situation and perceive the conflict between Israelis and Palestinians as inevitable from a historical perspective. Topics 2 to 4 discuss the various atrocities of war and concerns about genocide, with a final mention of hope for a ceasefire and peace.

In contrast, Middle East Eye's audience primarily consists of locals from the Middle East, and their perspectives differ from CNN's audience. The first topic focuses on concerns about Palestinian human rights, especially regarding the impact of war on hospitals and the harm caused to civilians by Israel's blockade on water and electricity. There is a strong desire for a ceasefire to protect human rights. Subsequent themes accuse Israel of various injustices in its rule over the Gaza Strip. The third theme discusses the disparity between Western media coverage of Israel and Hamas and local perceptions. Themes four to six, respectively, call for Western intervention, discuss the entry of the Israeli army into the Gaza Strip, and oppose genocide while supporting Palestinian statehood. The final theme condemns war and hopes for a better future.

Overall, there are significant differences in viewpoints between the audiences of CNN and Middle East Eye. However, both express a shared desire to uphold the human rights of Gaza residents and call for intervention from all parties to bring an end to the conflict as soon as possible. Furthermore, the content of audience discussions generally aligns with the short video news.

6. Conclusions

Short video platforms have become increasingly popular social media platforms, exerting a significant influence on human society. They are commonly used for commercial promotion, e-commerce, entertainment, education, and even news dissemination. In recent years, many researchers have focused on studying the impact of short videos, but there has been limited research on how to create popular short videos. Therefore, this study proposed an NLP-QFD model to determine the key success factors. A real case is collected from YouTube Shorts (CNN and Middle East Eye) to demonstrate the effectiveness of the proposed model. The research findings could provide guidance for future short video creators, especially for small-scale businesses, to produce successful short videos and expand their influence through social media.

The four key success factors (KSFs) identified in this study, namely Movie title, Promotion, Reviews, and Social Media, are common across companies of all sizes. This underscores the importance of understanding the characteristics and usage patterns of social media users in successfully promoting short videos. The titles of short videos must be compelling to attract viewers, and social media editors need to engage with the audience frequently and pay attention to reviews, using them to guide the direction when necessary. Additionally, even in short videos, it is essential to promote the company's brand to establish its image on social media platforms.

Regarding unique KSFs, for large companies, hiring celebrities such as actors or officials can enhance the credibility of short videos and strengthen users' trust in the company's brand. For smaller companies, leveraging factors such as Shooting and Music can be beneficial. Utilizing captivating shooting techniques and incorporating emotionally resonant or impactful background sounds or music can attract more viewers to watch short videos, thus increasing the likelihood of success.

Moreover, we can see from the view counts and audience comments that, although there is a significant difference in scale between CNN and Middle East Eye, Middle East Eye has successfully utilized the authenticity of its short videos. In particular, the poignant scenes of suffering of vulnerable groups such as women, children, the elderly, and mothers crying and in pain, as well as the destruction of hospitals and civilian homes, have generated similar effects to those of large media outlets such as CNN through social media dissemination.

To sum up, the findings of this study indicate that the key success factors for short videos include movie title, promotion, reviews, and social media. Short video creators need to invest a significant amount of effort in these elements to ensure effective viewership. Additionally, we found that endorsements by famous individuals are particularly important for large organizations. These large organizations typically have sufficient resources and credibility to enlist authoritative figures to enhance the credibility and authority of their short videos. On the other hand, music and shooting techniques are crucial success factors for small organizations in creating successful short videos. Small organizations can significantly enhance viewers' empathy and compassion by using touching background music or impactful, poignant sounds from news scenes, combined with first-person shooting techniques that make the audience feel as if they are experiencing the events firsthand, thereby eliciting more resonance.

Regarding research limitations and future works, this study proposed a new NLP-QFD method, which uses a quantitative approach to identify the key success factors of short videos. The effectiveness of this method is demonstrated using only two case studies from Western media (CNN) and regional media (Middle East Eye). However, this study only used two cases from Western media (CNN) and regional media (Middle East Eye). As we know, short videos on different platforms or of different types could have different key factors. To have a comprehensive result, future works can adopt our NLP-QFD method on different platforms (such as TikTok) and for various types of short videos (such as entertainment and live commerce videos). Lastly, what the authors want to convey is that we do not hold a specific stance on the conflict between the two sides. This study merely focuses on discovering the KSFs of short videos on social media from an academic research perspective, with the hope for world peace.

Author Contributions: Conceptualization, L.-S.C., H.-C.W. and C.-C.H.; methodology, L.-S.C. and C.-C.H.; software, C.-C.H. and H.-C.W.; validation, L.-S.C., W.-D.J. and H.-C.W..; formal analysis, C.-C.H. and L.-S.C.; investigation, C.-C.H. and H.-C.W.; resources, W.-D.J. and L.-S.C.; data curation, C.-C.H. and H.-C.W.; writing—original draft preparation, C.-C.H., H.-C.W. and W.-D.J.; writing—review and editing, L.-S.C.; visualization, H.-C.W. and C.-C.H.; supervision, L.-S.C.; project administration, L.-S.C.; funding acquisition, H.-C.W. and L.-S.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Science and Technology Council, Taiwan under grant No. NSTC 112-2410-H-324-004.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: This study was supported in part by the National Science and Technology Council, Taiwan (Grant No. NSTC 112-2410-H-324-004) and Chaoyang University of Technology.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Liu, M.; Zhuang, A.; Norvilitis, J.M.; Xiao, T. Usage patterns of short videos and social media among adolescents and psychological health: A latent profile analysis. *Comput. Hum. Behav.* **2024**, *151*, 108007. [CrossRef]
2. Yuan, Y.; Wang, Q. Characteristics, hotspots, and prospects of short video research: A review of papers published in China from 2012 to 2022. *Heliyon* **2024**, *10*, e24885. [CrossRef] [PubMed]
3. Cho, M.; Jeong, D.; Park, E. AMPS: Predicting popularity of short-form videos using multi-modal attention mechanisms in social media marketing environments. *J. Retail. Consum. Serv.* **2024**, *78*, 103778. [CrossRef]
4. Fang, X.; Xie, C.; Yu, J.; Huang, S.; Zhang, J. How do short-form travel videos trigger travel inspiration? Identifying and validating the driving factors. *Tour. Manag. Perspect.* **2023**, *47*, 101128. [CrossRef]
5. Lu, S.; Yu, M.; Wang, H. What matters for short videos' user engagement: A multiblock model with variable screening. *Expert Syst. Appl.* **2023**, *218*, 119542. [CrossRef]
6. Yin, X.; Li, J.; Si, H.; Wu, P. Attention marketing in fragmented entertainment: How advertising embedding influences purchase decision in short-form video apps. *J. Retail. Consum. Serv.* **2024**, *76*, 103572. [CrossRef]
7. Wang, Z.; Zhang, J.; Ji, S.; Meng, C.; Li, T.; Zheng, Y. Predicting and ranking box office revenue of movies based on big data. *Inf. Fusion J.* **2020**, *60*, 25–40. [CrossRef]
8. Verma, G.; Verma, H. Predicting Bollywood Movies Success Using Machine Learning Technique. In Proceedings of the 2019 Amity International Conference on Artificial Intelligence (AICAI), Dubai, United Arab Emirates, 4–6 February 2019; pp. 102–105.
9. Cizmeci, B.; Oguducu, S.G. Predicting IMDb Ratings of Pre-release Movies with Factorization Machines Using Social Media. In Proceedings of the 2018 3rd International Conference on Computer Science and Engineering (UBMK), Sarajevo, Bosnia and Herzegovina, 20–23 September 2018; pp. 173–178.
10. Bae, G.; Kim, H.-J. The impact of movie titles on box office success. *J. Bus. Res.* **2019**, *103*, 100–109. [CrossRef]
11. Jang, M.; Baek, H.; Kim, S. Movie characteristics as determinants of download-to-own performance in the Korean video-on-demand market. *Telecommun. Policy* **2021**, *45*, 102140. [CrossRef]
12. Munoz, I.B.; Liu-Zarzuela, J.; Oorjitham, N.; Jacob, D. YouTube and TikTok as a source of medical information on dissociative identity disorder. *J. Affect. Disord. Rep.* **2024**, *15*, 100707. [CrossRef]
13. Carpenter, J.P.; Morrison, S.A.; Shelton, C.C.; Clark, N.; Patel, S.; Toma-Harrold, D. How and why educators use TikTok: Come for the fun, stay for the learning? *Teach. Teach. Educ.* **2024**, *142*, 104530. [CrossRef]
14. Alcántara-Pilar, J.M.; Rodriguez-López, M.E.; Kalinić, Z.; Liébana-Cabanillas, F. From likes to loyalty: Exploring the impact of influencer credibility on purchase intentions in Tik-Tok. *J. Retail. Consum. Serv.* **2024**, *78*, 103709. [CrossRef]
15. Shoukat, M.H.; Selem, K.M.; Elgammal, I.; Ramkissoon, H.; Amponsah, M. Consequences of local culinary memorable experience: Evidence from TikTok influencers. *Acta Psychol.* **2023**, *238*, 103962. [CrossRef] [PubMed]
16. Kim, A.; Trimi, S.; Lee, S.G. Exploring the key success factors of films: A survival analysis approach. *Serv. Bus* **2021**, *15*, 613–638. [CrossRef]
17. Kim, E.; Kim, S. Online movie success in sequential markets: Determinants of video-on-demand film success in Korea. *Telemat. Inform.* **2017**, *34*, 987–995. [CrossRef]

18. Chen, M.-Y.; Chang, J.-R.; Chen, L.-S.; Chuang, Y.-J. Identifying the Key Successful Factors of Movie Projects in Crowdfunding. *Multimed. Tools Appl.* **2022**, *81*, 27711–27736. [CrossRef]
19. Liu, Q.; Lu, J.; Zhang, G.; Shen, T.; Zhang, Z.; Huang, H. Domain-specific meta-embedding with latent semantic structures. *Inf. Sci.* **2021**, *555*, 410–423. [CrossRef]
20. Ghosal, S.; Jain, A. Depression and Suicide Risk Detection on Social Media using fastText Embedding and XGBoost Classifier. *Procedia Comput. Sci.* **2023**, *218*, 1631–1639. [CrossRef]
21. Robertson, C.; Carney, J.; Trudell, S. Language about the future on social media as a novel marker of anxiety and depression: A big-data and experimental analysis. *Curr. Res. Behav. Sci.* **2023**, *4*, 100104. [CrossRef] [PubMed]
22. Krishnamurti, T.; Allen, K.; Hayani, L.; Rodriguez, S.; Davis, A.L. Identification of maternal depression risk from natural language collected in a mobile health app. *Procedia Comput. Sci.* **2022**, *206*, 132–140. [CrossRef]
23. Bhandarkar, A.R.; Arya, N.; Lin, K.K.; North, F.; Duvall, M.J.; Miller, N.E.; Pecina, J.L. Building a Natural Language Processing Artificial Intelligence to Predict Suicide-Related Events Based on Patient Portal Message Data. *Mayo Clin. Proc. Digit. Health* **2023**, *1*, 510–518. [CrossRef]
24. Mayopu, R.G.; Wang, Y.-Y.; Chen, L.-S. Exploring the advertising elements of electronic word-of-mouth in social media: An example of game reviews. *Multimed. Tools Appl.* 2024; *in press*. [CrossRef]
25. Mayopu, R.G.; Wang, Y.-Y.; Chen, L.-S. Analyzing Online Fake News Using Latent Semantic Analysis: Case of USA Election Campaign. *Big Data Cogn. Comput.* **2023**, *7*, 81. [CrossRef]
26. Huynh-Cam, T.T.; Chen, L.-S.; Le, H. Using Decision Trees and Random Forest Algorithms to Predict and Determine Factors Contributing to First-Year University Students' Learning Performance. *Algorithms* **2021**, *14*, 318. [CrossRef]
27. Chang, J.R.; Liang, H.-Y.; Chen, L.-S.; Chang, C.-W. Novel feature selection approaches for improving the performance of sentiment classification. *J. Ambient. Intell. Humaniz. Comput.* **2020**. [CrossRef]
28. Chen, W.-K.; Chen, L.-S.; Pan, Y.-T. A text mining-based framework to discover the important factors in text reviews for predicting the views of live streaming. *Appl. Soft Comput.* **2021**, *111*, 107704. [CrossRef]
29. Chang, J.-R.; Chen, M.-Y.; Chen, L.-S.; Tseng, S.-C. Why Customers Don't Revisit in Tourism and Hospitality Industry? *IEEE Access* **2019**, *7*, 146588–146606. [CrossRef]
30. Li, D.; Bi, Z.; Han, X.; Qu, Z.; Lyu, C. Extracting key topics from massive COVID-19 in-formation on social networks: An integrated deep learning and LDA framework. *High-Confid. Comput.* **2024**, *4*, 100213. [CrossRef]
31. Zou, T.; Guo, P.; Li, F.; Wu, Q. Research topic identification and trend prediction of China's energy policy: A combined LDA-ARIMA approach. *Renew. Energy* **2024**, *220*, 119619. [CrossRef]
32. Yu, D.; Fang, A.; Xu, Z. Topic research in fuzzy domain: Based on LDA topic modelling. *Inf. Sci.* **2023**, *648*, 119600. [CrossRef]
33. Wahid, J.A.; Shi, L.; Gao, Y.; Yang, B.; Wei, L.; Tao, Y.; Hussain, S.; Ayoub, M.; Yagoub, I. Topic2Labels: A framework to annotate and classify the social media data through LDA topics and deep learning models for crisis response. *Expert Syst. Appl.* **2022**, *195*, 116562. [CrossRef]
34. Chen, L.-S.; Liu, C.-H.; Hsu, C.-C.; Lin, C.-S. C-Kano Model: A New Approach for Discovering Attractive Quality Elements. *Total Qual. Manag. Bus. Excell.* **2010**, *21*, 1189–1214. [CrossRef]
35. Lin, C.-S.; Chen, L.-S.; Hsu, C.-C. An Innovative Approach for RFID Product Functions Development. *Expert Syst. Appl.* **2011**, *38*, 15523–15533. [CrossRef]
36. Manor, I.; Segev, E. The Mediatisation of MFAs: Diplomacy in the New Media Ecology. *Hague J. Dipl.* **2019**, *15*, 66–92. [CrossRef]
37. Atad, E.; Lev-On, A.; Yavetz, G. Diplomacy under fire: Engagement with governmental versus non-governmental messages on social media during armed conflicts. *Gov. Form. Q.* **2023**, *40*, 101835. [CrossRef]