How Media Influences Public Perception of AI Applications in Education-A Research on YouTube Comments

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Abstract: How do media influence public perception? In the growing field of AI applications in education, the audience's opinions and sentiments are becoming increasingly important, as they are closely related to the media agenda-setting process. Nowadays, as social media penetrates people's lives, the influence of media on audience cognition is becoming more extensive and in-depth. Using qualitative and quantitative methods, the article will research YouTube comments on related videos released by different types of channels: the official channels and personal channels. In this work, data science technology will assist in analyzing the themes and sentiments within public perception. The agenda-setting characteristics and effects of different types of channels will be described, and the framing theory will be integrated to aid the analysis process, providing a more comprehensive view of the interaction between the media agenda and the public agenda, helping education industry insiders or professionals involved in the situation of "Artificial Intelligence in Education" understand the audience's views.

Keywords: Agenda-Setting, Frame, YOUTUBE, Public Perception, Education

1. Introduction

In recent years, the application of AI technology in education has grown rapidly, and the impact it brings to education has received increasing attention. At the same time, social media and others are profoundly changing our lifestyles, work patterns, and social interactions. The question we are interested in is whether different social media agendas affect people's perceptions and sentiments about the impact of AI technologies on education. This research was focused on combing and analyzing the research results in related fields in the last 5 years, and this study proposes to investigate this question mainly by using multimodal social media data mining and analysis.

2. Literature review

2.1. Impact of artificial intelligence technology on education

In recent years, the application of artificial intelligence (AI) technology in education is growing rapidly. The applications of AI technology in education include providing customized learning experiences, dynamic assessment, and facilitating meaningful interactions in online, mobile, or blended learning environments [1].

The applications of AI in education are mainly focused on the following aspects: Reducing the workload of teachers. giving teachers more time to focus on teaching itself; providing customized learning content and teaching methods to personalize students' learning experience; revolutionizing assessment methods to provide more in-depth learning assessment; and intelligent tutoring systems (ITS) to enhance students' understanding of specific topics [1-3]. Although AI technology brings many opportunities for education, it is also accompanied by a series of risks and challenges, such as: data privacy and security issues, ethical issues, technology dependency issues, and educational equity issues with teachers' pedagogical responsibility and autonomy [2-5].

2.2. The effects of different media agendas on public

Social media significantly impacts individuals on multiple levels. Research has shown that the impact of social media on individuals is multifaceted and involves multiple domains such as decision-making, academic performance, mental health, and social behavior. The impact of social media on individuals is complex and multifaceted, with the potential for both positive outcomes, such as increased social connectedness and social capital and enhanced personal well-being, and negative impacts, such as mental health issues and social isolation. However, future research needs to further explore the complex relationship between social media use and individual impacts, and explore effective interventions to promote positive social media use. [6-7]

Researchers employed an emotion vocabulary ontology to categorize the types of emotions expressed in texts posted by the government, media, and public on social media. They used a machine learning model based on the naive Bayes algorithm to predict the emotional tendencies within these texts and analyzed the evolving emotional trends of different groups on social media. In addition, the dynamic effects and causal relationships of emotions among different subjects were investigated by vector autoregressive (VAR) modeling and Granger causality test. [6] The study shows that agenda-setting in different media has a multifaceted impact on people and is particularly significant at the emotional level.

2.3. Basic concepts

Official Media Most official media in the West are market-oriented and mainstream media. Because of their financial, funding and ownership links to governments, political parties or institutions and groups, they play the role of government mouthpiece at certain moments, and at certain moments they play the role of a voice for institutional interests.[8]

We-media The concept of "we-media" was first proposed by American writer Dan Gillmor in 2002, and in January 2003, he published "News for Next Generation: Here Comes 'We Media'" in Columbia *Journalism Review*, pointing out that due to the development of blogs, forums and other platforms, many members of the public do not consciously participate in the dialogue of news events. In July 2003, the Media Center of the American Press Institute published the "We Media" study, coauthored by Shayne Bowman and Chris Willis, which provided a clear scholarly explanation of we-media, defining it as: "We-media is a way for the general public to begin to understand how the general public delivers and shares their facts, their news, enhanced by digital technology and connected to the global body of knowledge. " Thus, the term "We- Media" entered the public consciousness.[9]

According to these definitions above, the concept “individual influencers” “personal channel” in our survey belongs to the category of we-media.

3. Purpose

Media play a complex role in influencing the audience's views and sentimental tendencies. The media plays an important role in the acceptance and feedback of AI policies in education.

Accordingly, this study aims to investigate the impact of media agenda setting on the audience's viewpoints as well as emotional and sentimental tendencies which further affects the enactment and implementation of related policies. This study takes YouTube users' comments based on different topics posted by official media and individual influencers under the topic of "AI in education" as the raw material, and through machine learning, describes the differences in the topics of the videos posted by different media types and explore their impact on users' opinions and emotional and mood colors.

The overarching research questions that guided the current study are as follows:

RQ1.Are there any differences in the themes that emerged when we consider the posting channels?

RQ2.Are there any differences in the distributions of sentiments and emotions emerging across the themes when considering the posting channels?

RQ3.How media agenda-setting influences audience perspectives?

4. Theoretical framework

4.1. Media agenda-setting theory

Origins & Development The origin of agenda-setting theory can be traced back to Lippmann's Public Opinion. Although Lippmann did not use the term "agenda-setting" in his book, he suggested that the mass media construct a "pseudo environment" for the public, linking "the world outside and pictures in our heads" (the world outside and pictures in our heads). the world outside and pictures in our heads".

The concept of "agenda setting" was first proposed by Maxwell McCombs and Donald Shaw during the 1968 U.S. election, and empirical research confirmed the high correlation between the media agenda and the public agenda. The mass media not only determines what the public thinks, but also influences how the public thinks. In 1972, they published *The Agenda-Setting Function of Mass Media*, which formally put forward the "agenda-setting theory", i.e., "the prominent coverage of an event or social issue by mass media in a certain period of time will arouse the public's interest in the issue. This is the first level of agenda-setting theory - issue agenda-setting, which focuses on the relationship between media issues and public issues.[10]

In 1997, McCombs and Shaw, in their study of the Spanish election, proposed that the perception of an object comes from the specific attributes of the object and that the media can give different attributes of the same issue different prominence through attribute agenda-setting to influence the public's "what to think", and took this as the second level of agenda-setting theory, namely, "attribute agenda-setting" theory, which focuses on the relationship between media agenda attributes and public agenda attributes.[10]

Scholars such as Lopez-Escobar E and McCombs point out that the attributes of media issues contain two dimensions: substantive attributes and affective attributes. Substantive attributes refer to the nature of the news that can help the public understand and identify different topics, which is similar to the framing effect of the media, and mainly constructs people's understanding of news events from the cognitive and behavioral levels; affective attributes refer to the nature of the news that can help the public to make judgments, which mainly affects people's value judgments from the level of affective attitudes, and include positive tone, negative tone, negative tone, and negative tone, which include positive tone, negative tone, and negative tone. Emotional attributes refer to the nature of the news that can help the public to make judgment, mainly affecting people's value judgment from the level of emotional attitude, including Positive tone, Negative tone and Neutral tone.[11] Figure 1 is a summary presentation of the above information.

Figure 1: Two levels of agenda setting

Media Shapes the Reality: Agenda-setting theory postulates, first proposed by McCombs and Shaw, that the mass media have a function of setting the "agenda" for the public. In choosing and displaying news, editors, newsroom staff, and broadcasters play an important part in shaping reality by giving different degrees of prominence to the various "issues", and that news reporting and information dissemination activities influence people's judgment of the "events" and importance of the world around them. Audience learns not only about a given issue, but also how much importance to attach to that issue from the amount of information in a news story and its position.

4.2. Framing theory

Origins & Development The concept of frame analysis was first introduced by the American sociologist Erving Goffman, and it has been used to examine how people interact in the process of constructing social reality. Entman argues that framing, as applied to news media reporting, is the process of selecting an aspect of reality and making it more salient in the text, and therefore the selection and salience of the news practitioner affects the perception of the audience. Tuchman recognizes that framing plays an integral role in the gathering of news material by media practitioners and the processing of news by audiences, i.e., "the organization of news frames into everyday reality."

According to Entman, news frames have four functions: defining problems, diagnosing causes, making moral judgments, and suggesting remedies. These four functions are also in line with the logical thinking structure of "what", "why", "how" and "how to do" that the public follows in the process of explaining practical problems. By filtering and emphasizing the framework, it can satisfy the public's need to understand the "what" in a cursory manner and to explore the "why" and "how" in depth, and at the same time enable the media to express their own attitudes and guide the public's behavior, i.e., the "what", "why", "how" and "how". At the same time, it also allows the media to express their attitude and guide public behavior, i.e., the "how".[8] Framing theory extends three core concepts in its formation and development - Frame, Framing and Framing Effect - which are widely used in news texts, news production and audience research [12].

Theory Embedding Rationale According to McCombs' interpretation, framing analysis is closely related to second level agenda setting, if defined in terms of the linguistic organization of attribute agenda setting, framing analysis refers to the selection and emphasis of certain specific attributes when talking about the object of the media agenda. Attribute agenda setting and framing are not equivalent, but studying the framing effect from the perspective of attribute agenda setting can provide a deeper understanding of the functioning mechanism of framing. In agenda setting research, related scholars often use frame analysis to construct categories and complete the analysis of media agenda setting. [10]

5. Research methodology

5.1. Mixed method

5.1.1. Digital ethnography

Digital ethnography, as an online research method focused on studying virtual communities and cultures, does provide a powerful tool for a powerful tool for understanding interactions and cultural phenomena in cyberspace. Cyberspace is composed of relationships between people and their interactions, and the process of the researcher entering this space is actually the process of establishing connections and interactions with the research object.[13]

Social media is a collective term for websites and applications that focus on communication, community-based input, interaction, content-sharing and collaboration. People use social media to stay in touch and interact with friends, family and various communities. YouTube, as a virtual community platform that provides a place for interaction and enables the researcher to enter the community space and gain a deeper understanding of the real thoughts and behaviors of the research subjects, provides feasibility for cyber ethnography as a research method.

In this study, firstly, after limiting the video topic to “AI in education”, 14 videos were selected. Secondly, the top six videos with the highest engagement were ranked based on the number of comments, views, and other metrics. By checking the quality of comments on the videos, we excluded the cases of water armies and unclear or meaningless meanings, so as to get the final five video products. The respective channel types are analyzed and categorized, and finally divided into two categories: official channels and individual influencers.

5.1.2. Content analysis method

American communication scholar Berelson believes that content analysis is a research method that describes the content of communication objectively, systematically and quantitatively. Through the content analysis method, we can clearly see the content characteristics and change trends of communication information. In this paper, we will use the content analysis method to collect the relevant reports under study, and then read the samples, construct categories according to the content, and interpret the text [8]

5.1.3. Textual analysis

To analyze the connotation of the text and show the characteristics of the text, so that the details of the text can be more carefully recognized. Through the text analysis method, it can deeply analyze the report text, analyze the connotation of the text, study the report framework, and more comprehensively understand and interpret the report content. The form of content analysis, supplemented by text analysis, can make up for the details neglected by the content analysis method which is purely centered on the construction of categories.[8]

5.1.4. MDCOR

Open-ended questions in survey research allow participants to respond freely using their own words.

YOUTUBE is a community platform that allows users to express their opinions freely. Responses to comments in YOUTUBE about “AI technology application in education” are open-ended responses.[14]

Machine driven classification approach relies on data science, data visualization, and natural language processing (NLP) tools for data labeling and classification, which could typically lose or alter participants' meanings or voices and could fall short in yielding nuanced understandings, during the process of text cleaning or preparation by normalization techniques such as lemmatization or stemming. [14]

MDCOR, as an analytic framework and free software tool, can solve these potential problems properly [14], which can classify vast amounts of qualitative evidence effectively and efficiently without altering the original voices of our research participants and while leveraging the nuances that human reasoning brings to the qualitative and mixed methods analytic tables. The technical principle behind this tool is LACOID (A Machine Learning-Based Integrative Framework [and Open-Source Software] to Classify Big Textual Data, Rebuild Contextualized/Unaltered Meanings, and Avoid Aggregation Bias), which is an integration of MACOID (Machine Learning Code Identification) and HUCOID (Human Code Identification). After fully integrating with the qualitative analysis of this classified, unaltered, and contextualized qualitative information, the output can be built from machine learning and text classification analyses of qualitative evidence. The genuine voices of participants, as presented in their research contributions, need to be preserved in their original, unaltered text, including the specific context and position within the discourse.[15]

5.1.5. SENA

SENA is an open-sourced platform for Sentiment Analysis.[16] Sentiment analysis and opinion mining is the field of study that analyzes people's opinions, sentiments, evaluations, attitudes, and emotions from written language by determine the polarity. The growing importance of sentiment analysis coincides with the growth of social media such as reviews, forum discussions, blogs, micro-blogs, Twitter, and social networks.[17] Methodologically, the text is automatically assessed to determine if the expressed sentiment is positive, negative, or neutral.

5.1.6. Thematic analysis

Thematic analysis is a qualitative research method that can be widely used across a range of epistemologies and research questions. It is a method for identifying, analyzing, organizing, describing, and reporting themes found within a data set. Boyatzis described thematic analysis as a translator for those speaking the languages of qualitative and quantitative analysis, enabling researchers who use different research methods to communicate with each other. [18]

As thematic analysis does not require the detailed theoretical and technological knowledge of other qualitative approaches, it offers a more accessible form of analysis, particularly for those early in their research career [18]

By coding, researchers move from unstructured data to the development of ideas about what is going on in the data [19], during which the researchers identify important sections of text and attach labels to index them as they relate to a theme or issue in the data [20].

6. Data collection

6.1. Data cleaning

The raw YouTube data obtained in the previous step contains confusing data, noisy words, etc. That will influence the result of the following data analysis. Therefore, the data cleaning process has to be done.

Procedure one shows how to eliminate irrelevant comments. The comments can be divided into two types: "main comments" and "the replies to the main comments". The pre-research points out that most replies respond to their main comments instead of video content. Therefore, those replies are noise for the research and need to be deleted. The files from YouTube API have a column named “ParentID”, which records the parent comments of this comment. If the ParentID is NULL, means this comment has no parent comments, it is a main comment, and we need to include it. Otherwise, if the comment has parent comments, it should be deleted. Use code “Delete Replies” to eliminate replies. YouTube Data is a data frame we got in the previous step; you must make sure the column name has not been changed.

```
youtubeData <- youtubeData[is.na(youtubeData$ParentID)]
```

Procedure 1: Remove Replies

Procedure 2 shows how to process emoji, which are visual symbols in computer mediated communication (CMC). Because they are non-verbal cues with rich emotional meanings, emojis are an important medium for interaction and emotional communication on the Internet.[21] Emojis cannot be recognized in the following data analysis since the tools used can only manage English characters. In this case, the function “replace-emoji” in the package lexicon [22] has been used to transform emoji into corresponding English phrases so that machines can correctly recognize the meaning of emoji and analyze them in the following steps.

```
YoutubeData$Comment <- replace_emoji(YoutubeData$Comment, emoji_dt = lexicon::hash_emojis)
```

Procedure 2: Emoji Processing

Procedure three shows how to exclude all elements except text. The punctuation will hamper the following machine process. For example, the MDCOR that will be mentioned below will record ‘people’ and ‘people.’ as two different words but they are the same. With the use of the function “str_remove_all” in the package stringr [23], all the text other than numbers, lowercase letters, and uppercase letters are eliminated. Anything such as commas, periods, and random symbols such as dollar signs will be deleted. What's left is pure text.

```
before_renamed_csv$text <- str_remove_all(before_renamed_csv$text,"[A[\\da-zA-Z ]]")
```

Procedure 3: Remove unexpected characters

Procedure four is to exclude the stopwords. The stopwords may be identified as a word that has the same likelihood of occurring in those documents not relevant to a query as in those documents relevant to the query [24] which will not contribute to the research target. In the treating procedure, the words ‘it’, ‘is’, and other stopwords in comments do not contribute to expressing people’s emotions or sentiments. The column “Comment” has been transformed into the corpus, and with the use of the R package tm [25] The stopwords can be deleted.

Procedure five is to replace the video links with corresponding meaningful video titles. For better identification of videos in the following procedure, the video links should be replaced by corresponding meaningful video titles. Using the “Mutate” method in the package dplyr [26]. these unreadable YouTube links have been transformed into the generalization of the videos.

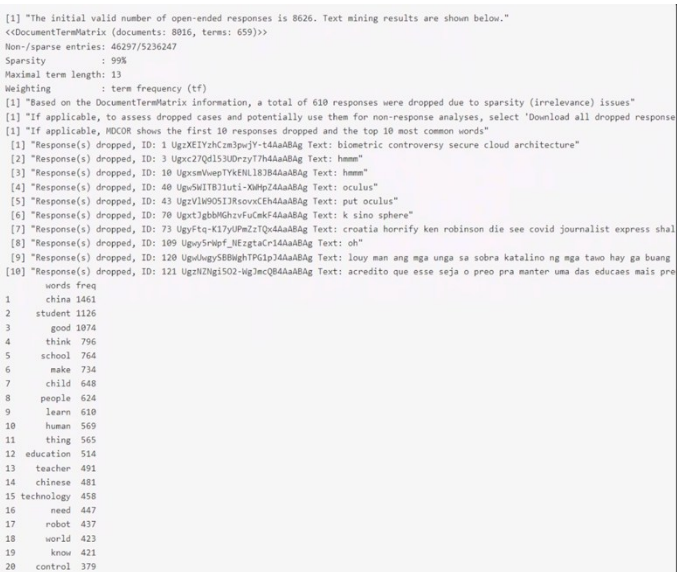
6.2. Data interpretation

In the data analysis part, the research aims to interpret data based on the benchmark and description given in the previous section. Since the research aim is to find differences that lie in different channels, the official channel and personal channel are being processed separately. The analysis part will be separated by the two different apps used.

With the data as CSV format being uploaded into MDCOR, several options can be used to produce the information and graphs we need to validate our hypothesis. The MDCOR will produce information and graph as follow: Text mining via optimal topic/theme detection using Gibbs sampling, Markov chain Monte Carlo, and latent Dirichlet allocation distributions; data visualization such as interim distance maps and metrics; and data mining and classification [14]

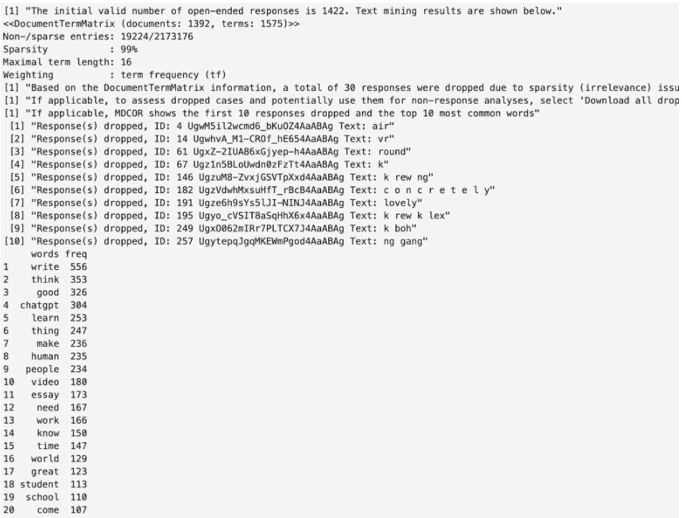
6.2.1. Text mining

The first output shown in the MDCOR would be text mining. Namely, it is the descending order of words appearing in the selected 'text' column by frequency. In the case that fits the key word in the RQ "different channels", comments in the official channel and personal channel are being separated and conducted two trials inside the MDCOR.



```
[1] "The initial valid number of open-ended responses is 8626. Text mining results are shown below."
<<DocumentTermMatrix (documents: 8016, terms: 659)>>
Non-/sparse entries: 46297/5236247
Sparsity           : 99%
Maximal term length: 13
Weighting          : term frequency (tf)
[1] "Based on the DocumentTermMatrix information, a total of 610 responses were dropped due to sparsity (irrelevance) issues"
[1] "If applicable, to assess dropped cases and potentially use them for non-response analyses, select 'Download all dropped response
[1] "If applicable, MDCOR shows the first 10 responses dropped and the top 10 most common words"
 [1] "Response(s) dropped, ID: 1 UgzXEIYzhCzm3pwjY-t4AaABAg Text: biometric controversy secure cloud architecture"
 [2] "Response(s) dropped, ID: 3 Ugxc27Qd153UDrzyT7h4AaABAg Text: hmmm"
 [3] "Response(s) dropped, ID: 10 UgxsmVwepTYkENL18JB4AaABAg Text: hmmm"
 [4] "Response(s) dropped, ID: 40 Ugw5WITBJ1uti-XWHpZ4AaABAg Text: oculus"
 [5] "Response(s) dropped, ID: 43 UgzVlW905IJRsovxCEh4AaABAg Text: put oculus"
 [6] "Response(s) dropped, ID: 70 UgxtJgbbMGhzvFuCmkF4AaABAg Text: k sino sphere"
 [7] "Response(s) dropped, ID: 73 UgyFtq-K17yUPmZzTQx4AaABAg Text: croatia horrify ken robinson die see covid journalist express shal
 [8] "Response(s) dropped, ID: 109 Ugwy5rWpf_NEzgtaCr14AaABAg Text: oh"
 [9] "Response(s) dropped, ID: 120 UgwUwgySBBWghTPG1pJ4AaABAg Text: louy man ang mga unga sa sobra katalino ng mga tawo hay ga buang
[10] "Response(s) dropped, ID: 121 UgzNZNgi5O2-WgJmcQB4AaABAg Text: acredito que esse seja o preo pra manter uma das educaes mais pre
        words freq
1       china 1461
2     student 1126
3        good 1074
4       think  796
5      school  764
6        make  734
7       child  648
8      people  624
9       learn  610
10      human  569
11      thing  565
12  education  514
13    teacher  491
14    chinese  481
15 technology  458
16       need  447
17      robot  437
18      world  423
19       know  421
20    control  379
```

Figure 2: Text mining result of the official channel



```
[1] "The initial valid number of open-ended responses is 1422. Text mining results are shown below."
<<DocumentTermMatrix (documents: 1392, terms: 1575)>>
Non-/sparse entries: 19224/2173176
Sparsity           : 99%
Maximal term length: 16
Weighting          : term frequency (tf)
[1] "Based on the DocumentTermMatrix information, a total of 30 responses were dropped due to sparsity (irrelevance) issu
[1] "If applicable, to assess dropped cases and potentially use them for non-response analyses, select 'Download all drop
[1] "If applicable, MDCOR shows the first 10 responses dropped and the top 10 most common words"
 [1] "Response(s) dropped, ID: 4 UgwM5il2wcmd6_bKuOZ4AaABAg Text: air"
 [2] "Response(s) dropped, ID: 14 UgwhvA_M1-CROf_hE654AaABAg Text: vr"
 [3] "Response(s) dropped, ID: 61 UgxZ-2IUA86xGjyep-h4AaABAg Text: round"
 [4] "Response(s) dropped, ID: 67 Ugz1n5BLoUwdn0zFzTt4AaABAg Text: k"
 [5] "Response(s) dropped, ID: 146 UgzuM8-ZvxjGSVTpXxd4AaABAg Text: k rew ng"
 [6] "Response(s) dropped, ID: 182 UgzVdwhMxsuHfT_rBcB4AaABAg Text: c o n c r e t e l y"
 [7] "Response(s) dropped, ID: 191 Ugze6h9sYs5lJI-NINJ4AaABAg Text: lovely"
 [8] "Response(s) dropped, ID: 195 Ugyo_cVSIT8aSqHhX6x4AaABAg Text: k rew k lex"
 [9] "Response(s) dropped, ID: 249 UgxO062mIRr7PLTCX7J4AaABAg Text: k boh"
[10] "Response(s) dropped, ID: 257 UgytepqJgqMKEWmPgod4AaABAg Text: ng gang"
     words freq
1    write  556
2    think  353
3     good  326
4  chatgpt  304
5    learn  253
6    thing  247
7     make  236
8    human  235
9   people  234
10   video  180
11   essay  173
12    need  167
13    work  166
14    know  150
15    time  147
16   world  129
17   great  123
18 student  113
19  school  110
20    come  107
```

Figure 3: Text mining result of the personal channel

The text mining process also contributes to the overall robustness of the data by excluding comments in languages other than English, such as Spanish and other unclassified languages [14].

For example, as shown in Figure 2: Text Mining Result of the Official Channel, one of the dropped responses with ID 121 comments in Spanish. These responses are regarded as outliers, as they cannot affect the overall performance of the dataset but decrease the robustness of the data. Excluding these responses would enhance the clarity of the dataset. Same operation is applied in personal channel database as shown in Figure 3.

6.2.2. Trim common words

A typical problem that researchers face is having words that do not have actual meanings in the text-mining output. As shown by the two figures above, some words are useless. MDCOR offers the trim function in which these words can be deleted in the researcher's preferences.

```
<<DocumentTermMatrix (documents: 7985, terms: 656)>>
Non-/sparse entries: 44801/5193359
Sparsity           : 99%
Maximal term length: 13
Weighting          : term frequency (tf)
        words freq
1       china 1461
2     student 1126
3        good 1074
4       think  796
5      school  764
6       child  648
7      people  624
8       learn  610
9       human  569
10  education  514
11    teacher  491
12    chinese  481
13 technology  458
14      robot  437
15      world  423
16       know  421
17    control  379
18       time  370
19       want  366
20     parent  343
```

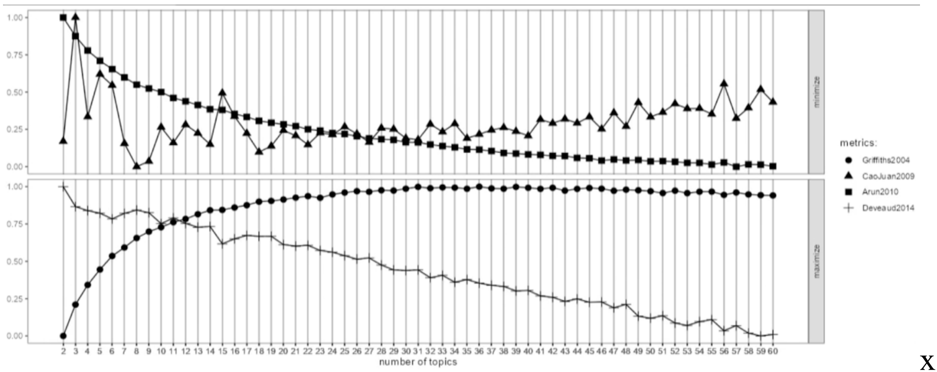
```
<<DocumentTermMatrix (documents: 1391, terms: 1572)>>
Non-/sparse entries: 18836/2167816
Sparsity           : 99%
Maximal term length: 16
Weighting          : term frequency (tf)
        words freq
1       write  556
2       think  353
3        good  326
4     chatgpt  304
5       learn  253
6       thing  247
7       human  235
8      people  234
9       video  180
10      essay  173
11       work  166
12       know  150
13       time  147
14      world  129
15      great  123
16    student  113
17     school  110
18     create  103
19      still  103
20 understand  103
```

Figure 4: Trimmed result of the official and personal channel

For official channels (see Figure 4), words "make", "thing", "need" are trimmed, as they are believed to produce no large effect upon the result of the metrics and sentimental analysis. For personal channels (see Figure 4), words "make", "need", "come" are trimmed, as they are believed to produce no large effect upon the result of the metrics and sentimental analysis.

6.2.3. LDA-based topic modelling metrics

In this study, 7985 comments regarding people's opinions about AI in education in the official channel and 1391 of that in the personal channel have been gathered. After trimming the words, MDCOR offers a metrics of four algorithms for researchers to determine the optimal topics for analysis: Griffiths 2004, CaoJuan2009, Arun2010, and Deveaud 2014. Two graphs are plotted with correlation of similarity and dissimilarity in different numbers of topics to test what is the optimal number of topics. What we need to do is finding the number of topics that show the smallest distance between the two graphs, or the number of topics that show the biggest dissimilarity and smallest similarity. In this case, the correlation between the supposed topics will be minimized - this will lead to clarity in the latter data storytelling work. The optimal situation is that the four lines are joined together, indicating a best solution to separate the words into topics; but in this research, the correlation can only be observed in two of the algorithms. Thus, our results are based on the analysis of Arun2010 and Deveaud2014.



x

Figure 5: Metrics plot of the official channel

As shown in Figure 5, an optimal choice of 2 topics was observed in the metrics plot of the official channel. Additionally, as the graph has shown, the score of having 8 topics is very close to that of 2 topics. Due to the workload of data interpretation, the former has been chosen as the main focus, and the 8-topic analysis is put as back-up.

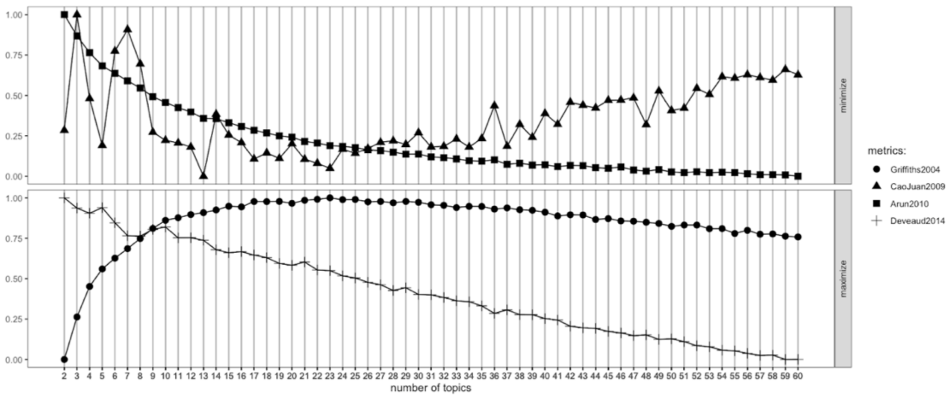


Figure 6: Metrics plot of the personal channel

As shown in Figure 6, in the metrics plot of the personal channel, the optimal number of topics observed is 4, and because the graph does not produce any close matches, we used 4 topic analysis in the later data interpretation process.

6.2.4. Intertopic distance map

Based on the metrics plot, the optimal number of topics can be determined. The optimal number of topics means the number of topics that can cover the comments, while having the least similarity as possible [15]. By accessing the intertopic distance map, the topics will be visualized in the form of circles. In this case study, the optimal situation appears when the separated topics do not collide with each other, and stay as far as they can be with each other. In this case, the topics separated have no correlation with each other, thus it is easier for the later topic generalization and data interpretation.

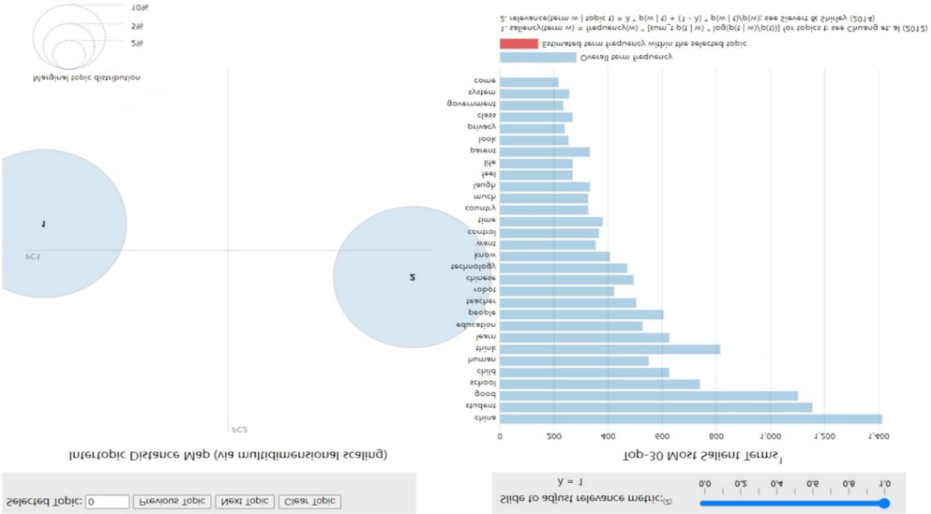


Figure 7: Intertopic distance map of the official channel

As shown in Figure 7, topic 1 and 2 stands at the left and right side of the coordinate system, separated by the PC2 axis. This provides a strong basis that the two topics have extremely low correlation with each other

As shown in Figure 8, topic 1 to 4 stands at the four corners in the coordinate system. As scholars have shown, topics located at the corners of the plane have contents that are more unique and discernable[15]. Thus, the four topics generated by the personal channel are believed to not collide with each other.

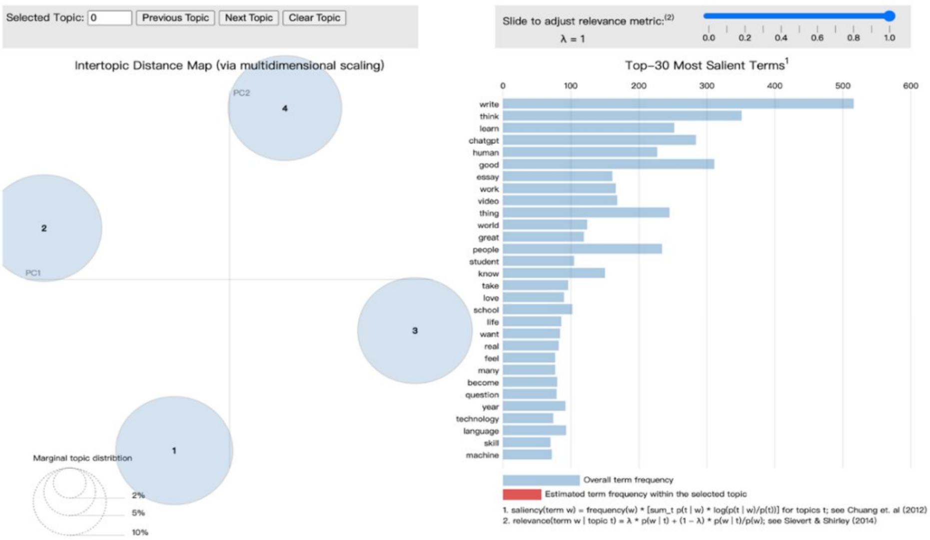


Figure 8: Intertopic distance map of the personal channel

6.2.5. MDCOR output & most representative comments

After generating the intertopic distance map, MDCOR gives back to files. The first is a csv that resembles the processed data. Researchers can use the csv as the base while doing sentimental analysis, namely, SENA. The second is a csv containing the most representative comments for different topics. As done by other researchers, the priority is to assess the validity of the separated topics. This can be done by assessing the metrics plot and the intertopic distance maps, with reference to the coherence and relevance of topics; Next, human classification played a pivotal role in distinguishing the differences and making synopsis of different topics. Specifically, by getting some of the most representative comments in different topics, researchers should be able to analyze what topics are about [14][27]. This research follows the same process by analyzing the topics based on two of the most representative comments.

6.2.6. Chi-square graphs

As shown in Figure 9, The chi-square graph shows the correlation between different topics and different videos. According to the chi-square graph, 0, or white box, can be interpreted as no correlation between the topic and video. When the numbers get bigger, the color changes from white to purple, indicating a relatively strong correlation, to blue, indicating a strong correlation; in contrast, when the number gets smaller, the color changes from white to pink, indicating relatively dissimilarity, to red, indicating strong dissimilarity.

6.2.7. Word cloud

After changing the given TXT file into a csv file, SENA is able to interpret and process the processed data. It will provide word frequencies and trimming functions similar to that of MDCOR. After executing SENA, several pages will be loaded as html in the local web browser. The first is the word cloud. It consists of words in different colors and sizes. The colors are randomly distributed. The sizes are biggest in the middle, and smaller spreading from all sides. As shown in Figure 10, Words in bigger sizes means higher frequency. Using the word cloud, interpretations can be made about different channels' words frequency, as well as most representative words or phrases.

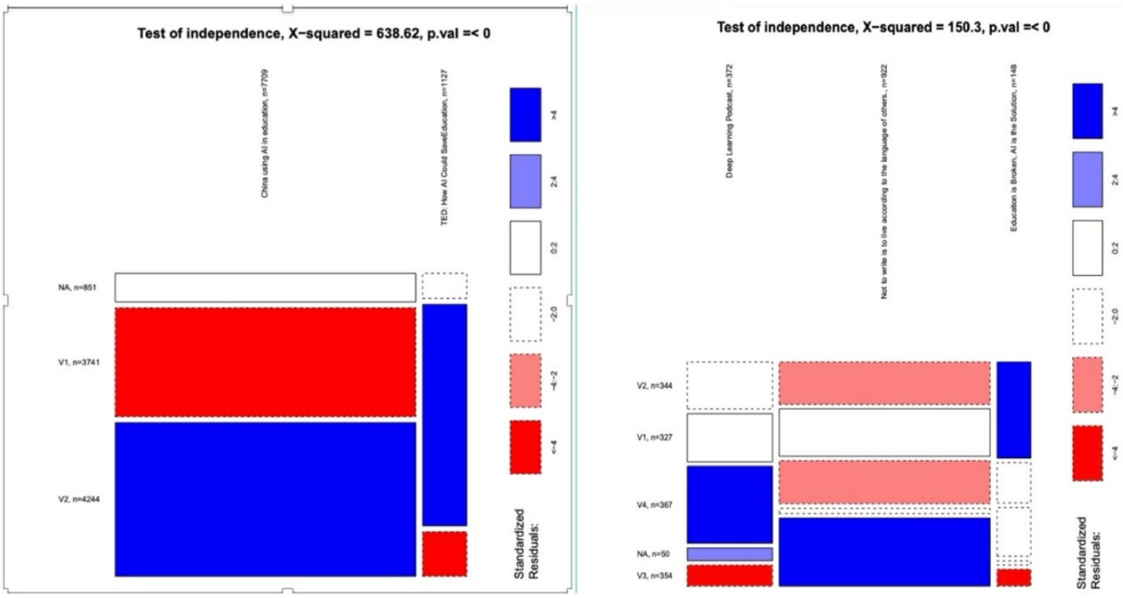


Figure 9: Chi-square graph of the official and personal channel

Figure 10: Official and personal channel word cloud

6.2.8. Sentiment histogram

The sentiment histogram is done by applying sentiment analysis to the dataset given. As shown in Figure 11 and Figure 12 ,12 kinds of sentiments are shown. With a higher intensity, the sentiments will result in a higher score on the histogram than other sentiments. Additionally, in different channels, the sentiment level of different topics is different, giving researchers a more comprehensive view of the data.

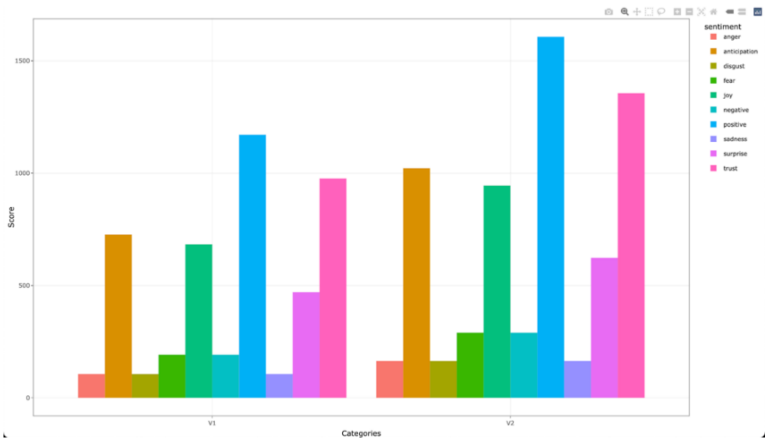


Figure 11: Official channel sentiment histogram

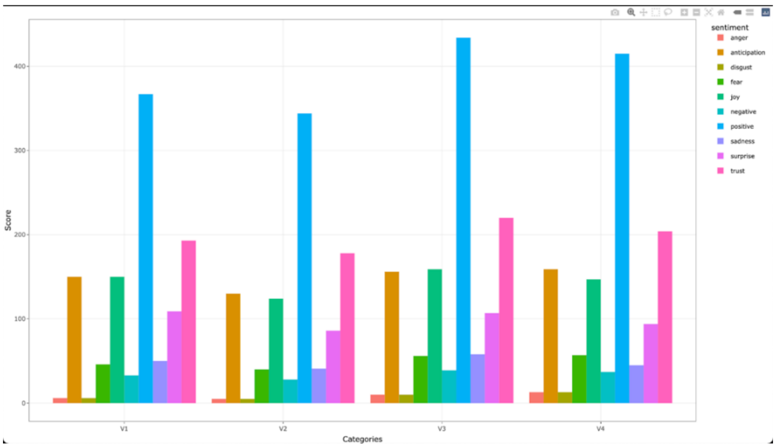


Figure 12: Personal channel sentiment histogram

7. Discussion: how media agenda-setting works

Framing theory works with different media issues. Entman summarized the four major frames of news reporting, which are Problem Definition, Causal Identification, Moral Judgement and Remedy Endorsement.[28]

Based on previous studies in the academic field, this study determines a specific framework for the theme of "AI Application in Education", taking into account the nature of the topic of this study, the development process, controversial points, etc. The research conducts content analysis of media reports on the subject of publication, theme, source, reporting stance and tendency, keywords, emotional color, and value expression.[8]

7.1. Analysis framework: analysis of media agenda side

7.1.1. Content attributes: category construction

In general, framing is the process of constructing meaning, guiding cognition and reflecting reality through words and texts. Different descriptions of the same information and different styles of wording can construct different meanings, affecting the audience's mentality and attitude, and thus guiding their behavior and decision-making. It selects, reorganizes, excludes, packages, processes and reshapes the information received by individuals in the objective world, and ultimately forms their subjective perceptions of the objective world. This mechanism is not only reflected in people's understanding of daily life, but also in the planning of news topics and the promotion of media agenda setting [8].

Table 1 shows the specific way of category construction with its criteria for judgment.

Table 1: Category construction [28]

First category	Secondary category	Specific criteria for judgment
Coverage	Real frame	Define the use and impact of AI technology in education and provide evidence, such as a description of the source or expert's background.
	Hoax frame	Challenge behaviors related to the application of AI technology in education, or challenge ideas around this application, such as dialectical thinking and other elements.
	Cause frame	Explanation of the reasons for the phenomenon of the application of AI technology in education, such as the inevitability and importance of that application.
	Impact frame	Formulate and make judgments about the results and impacts of the application of AI technology in education.
	Action frame	To express and provide suggestions and measures on how to cope with or address the impact of the application of AI technology in the field of education.

7.1.2. Content attributes: visual frames

For video communities such as YOUTUBE, the channel publishes works in which text and visuals coexist. Images tend to be more powerful framing tools due to their attributes of being close to reality and creating strong emotions. [29] Therefore, visual framing is one of the most important elements in the study of media agenda setting. Visual framing can be categorized into Stylistic level of framing, Denotative level of framing, Connotative level of framing and Ideological level of framing, which answer the question of visual framing respectively,which answer the four questions of subject, theme, social meaning and ideology expressed by visual elements and these four levels can be used for visual framing analysis, both in media framing and audience framing.[29]

Among them, the Stylistic level of framing and the Denotative level of framing are analyzed mainly in the form of captions and videos. The video form contains the use of a large number of visual elements, such as adding emoticons, subtitles, pictures, various kinds of screen effects and sound effects. Connotative imagery belongs to the Connotative level of framing, which means that the information conveyed by the visual media does not only include specific people, places, events, etc., but also embodies ideas or concepts related to them[8][29-30].

7.1.3. Sentimental attributes

Video Content Narrative Emotional Judgment

1) Positive narrative: the overall style of the short video is mainly positive, such as the help brought by teaching aids developed based on generative AI technology and so on.

2) Negative narrative: the overall style of the short video is predominantly negative, such as AI monitoring technology puts too much pressure on students, AI technology helps students cheat, etc.

7.2. Analysis of media agenda side

Comparison of media agenda setting among different media types

In this study, based on the criteria of class construction and sentiment attribute judgment of content attributes in the research design, i.e., using framing theory to assist the analysis, two video reports released by the official media and three video reports released by the self-media bloggers were subjected to content analysis and textual analysis, and how agenda-setting was carried out by the official media and self-media media under the topic of "Application of AI technology in the field of education".

7.2.1. First level of agenda setting

Table 2 contains two videos released by the official channel in the sample:

Table 2: Basic information of videos from official channels

Title	Channel	Channel Introduction
How China Is Using Artificial Intelligence in Classrooms | WSJ	Official The Wall Street Journal	The Wall Street Journal takes you inside carefully selected stories and events in a visually captivating way so you can dig deeper into the news and insights that matter to you. insights that matter to you.
How AI Could Save (Not Destroy) Education | Sal Khan | TED	Official TED	The TED Talks channel features the best talks and performances from the TED Conference, where the world's leading thinkers and doers give the talk of their lives in 18 minutes (or less). lives in 18 minutes (or less). Look for talks on Technology, Entertainment and Design -- plus science, business, global issues, the arts and more. You're welcome to link to or embed You're welcome to link to or embed these videos, forward them to others and share these ideas with people you know.

Table3 contains three videos posted by we-media channel in the sample:

Table 3: Basic information of videos from personal channels

Title	Channel	Channel Introduction
Andrew Ng: Deep Learning, Education, and Real-World AI	Lex Fridman	Lex Fridman broadcast and other videos.
Education is Broken & AI is the Solution	Peter H. Diamandis	Peter H. Diamandis is the co-author of the best-selling book "Abundance: The Future is Better Than You Think" and a speaker, engineer, physician and entrepreneur best known for being the founder and chairman of the X PRIZE Foundation and the co-founder and chairman of Singularity University. entrepreneur best known for being the founder and chairman of the X PRIZE Foundation and the co-founder and chairman of Singularity University.
The Real Danger of ChatGPT	Nerdwriter1	The Nerdwriter is a video series about art and culture.

At the level of topic selection, there is a certain degree of difference between official media and self-published media, with different types of media giving different types of topics prominence.

The Wall Street Journal, a politically inclined in-depth media outlet, focused on the application of AI technology in China's education sector; TED, a cutting-edge popularization organization in the fields of education, science, technology, business, and the arts, focused on the question of whether the impact of AI on the education sector is good or bad.

Lex Fridman and Peter H. Diamandis are both self-published bloggers who engage in podcasting. Their selections are similar in that they both explore the views of a particular expert. Nerdwriter1, on the other hand, focuses on art and culture in a more playful style with illustrations. It chose as its theme the adverse effects of ChatGPT on people's self-discovery.

It is worth noting that the official media has a wider range of topics, a more ambitious thematic setting, and a video content that is tightly focused on the main theme. There are some hidden purposes behind the selected topics, such as national competition and product promotion. In contrast, the self-media bloggers' topic selection is more refined, tending to analyze the topic of "Artificial Intelligence in Education" in certain extended areas. Humanistic concern is stronger, focusing on the proximity of the content to the public[31]; the structure of the content is more diffuse, not tightly focused on the topic. This is due to the fact that the self-media are easily influenced by profit-making goals, and report more on irrelevant and marginal information that is weakly related to the event, which leads to the deviation of topic selection and makes the agenda setting biased. [32]

7.2.2. Second level of agenda setting

Visual framework analysis:

In terms of headline form, official media headlines are more rigorous, have a clear statement structure, express meaning directly, and have standardized but not vivid language. Self-media, on the other hand, tends to use words containing labeling, suggestive words, and strong emotional color. For example, "collapse" and "real danger". [33]

From the perspective of video form, the video elements utilized by the official media are relatively single. It mostly utilizes interview materials, expert opinions, data charts and other elements to illustrate the facts, but this does not mean that the official media really maintains neutrality when expressing its views, but rather renders its views with facts. In contrast, the self media use more rich video elements, such as

The use of all kinds of illustration pictures, sound effects, emoticons, screen effects, etc., reflecting the fun of the video, strong visual impact, attracting the audience at the same time, convenient for the audience to understand the point of view.

In addition, the text structure of the official media video is clearer, the editing rhythm is more appropriate, and the explanation of technical terms and proper nouns is more thorough, which improves the credibility of the viewpoints. On the other hand, self-media videos have a more casual structure, such as podcasts to exchange views, with less control over the editing rhythm, and interesting and vivid texts.

Exploring the connotation levels of the two types of media videos, it can be found that the difference between the two media types has similar characteristics as the difference between the topic choices. The imagery conveyed by the official media is more ambitious, such as privacy protection, children's development, school education, international competition, and so on. Self-media, on the other hand, covers imagery that is more personal and humanistic, such as the ability to learn, self-discovery, and so on.

Content framework analysis:

By constructing and analyzing the categories of these five frames, the truth and deception frames focus on whether the extended content related to “AI Application in Education” is worthy of public attention, while the cause, consequence and action frames focus on how to respond to the known developments or challenges.[34]

Table4 and Table5 show the analysis of the content attributes based on the two videos released by the official medium in the sample:

Table 4: Specific analysis of video “How China Is Using Artificial Intelligence in Classrooms | WSJ”

Video Title	First class	secondary category	Existence of agenda-setting	Evidence of specific judgments	specificities
How China Is Using Artificial Intelligence in Classrooms | WSJ	Coverage	Real frame	be	State and summarize the methods and roles of AI technology used in Chinese classrooms	In-depth reporting Variety of interview subjects Predominantly negative reporting
		Hoax frame	be	Questioning the flaws in EEG technology behind attention level detection and data protection issues	
		Cause frame	be	Emphasize parents' and teachers' demands for student achievement	

Table 4: (continued)

		Impact frame	be	Predominantly negative impacts:AI technology has improved student performance to some extent, but has caused problems such as excessive stress and unprotected data	
		Action frame	clogged	No solution to the problem	

Table 5: Specific analysis of video "How AI Could Save (Not Destroy) Education | Sal Khan | TED"

Video Title	First class	secondary category	Existence of agenda-setting	Evidence of specific judgments	specificities
How AI Could Save (Not Destroy) Education | Sal Khan | TED	Coverage	Real frame	be	Presenting the problem facing the education industry now: AI helps students cheat and undermines the education system	Mainly focuses on showing positive impacts and is vague about negative impacts The main idea of the video is to introduce how Khanmigo, the educational chatbot, solves problems and looks at the future development
		Hoax frame	clogged	A one-sided introduction to the progressive nature of the chatbot Khanmigo	
		Cause frame	be	Explain the inevitability of the technological revolution and call for the active participation of the audience	
		Impact frame	be	Mainly focuses on showing positive impacts and is vague about negative impacts	
		Action frame	be	The main idea of the video is to introduce how educational chatbot, solves problems and looks at the future development	

Table6 Table7 and Table8 show the analysis of the content attributes based on the three videos posted by the self-published bloggers in the sample:

Table 6: Specific analysis of video “Andrew Ng: Deep Learning, Education, and Real-World AI | Lex Fridman Podcast #73”

Video Title	First class	secondary category	Existence of agenda-setting	Evidence of specific judgments	specificities
Andrew Ng: Deep Learning, Education, and Real-World AI | Lex Fridman Podcast #73	Coverage	Real frame	be	Introduction to the history and current status of artificial intelligence and early education	Positive emotions prevail Lack of discussion of negative information Focus on emphasizing the theme of deep learning
		Hoax frame	clogged	Presenting only AI to help deep learning lacks dialectical thinking	
		Cause frame	be	Introducing the inevitability and importance of the use of human performance in education	
		Impact frame	be	Embodying Deep Learning for Career and Degree Attainment	
		Action frame	be	Guidance on how to learn deeply	

Table 7: Specific analysis of video “Education is Broken & AI is the Solution w/ Mo Gawdat”

Video Title	First class	secondary category	Existence of agenda-setting	Evidence of specific judgments	specificities
Education is Broken & AI is the Solution w/ Mo Gawdat	Coverage	Real frame	be	Acknowledging Reality: 2025-2029 AI Will Reach Human Levels, Today's Education System Is Inadequate to Face the Coming Era	Focus: How Education Reform Can Adapt to the Inevitable Age of AI Information is more diffuse and detailed, loosely organized around the
		Hoax frame	be	Questioning the education system: "These are not the things that are taught in schools"	
		Cause frame	clogged	Lack of reasons for the application of AI technology to face the methodology	
		Impact frame	be	Illustrating the uncertainty that AI technology brings to life	
		Action frame	be	Suggest four skills that young people need to have	

Table 8: Specific analysis of video “The Real Danger of ChatGPT”

Video Title	First class	secondary category	Existence of agenda-setting	Evidence of specific judgments	specificities
The Real Danger of ChatGPT	Coverage	Real frame	be	The idea that ChatGPT's impact is overstated, when in fact its main power is in generating text.	Fun and visual Insufficiently articulate and in-depth
		Hoax frame	be	Questioning existing perceptions of ChatGPT's impacts	
		Cause frame	be	Explaining the Relationship Between the Popularity of Artificial Intelligence Writing and the Decline of Memory Teaching Methods	
		Impact frame	be	The popularity of artificial intelligence essay writing makes people work tend as editors tweakers embellishers	
		Action frame	clogged	No measures are explicitly proposed, but merely an expression of hope.	

Sentimental Framework

Linking the content frame and visual frame to the affective attributes can lead to the rationalization of the affective frame determination conclusion. Tables 5 and 6 are the only two videos with positively dominant affective tendencies. Their common point is the lack of agenda setting in the deception frame latitude, i.e., there is no questioning and criticism of the situation and viewpoints related to “AI Application in Education” shown in the respective videos, and there is a lack of discussion of the negative information. In addition, the two videos have a high proportion of agenda setting at the action framework level, which provides guidance and advice to the audience for future actions and gives them hope.

In the sample of this study, most of the video works are biased negative narratives. In the agenda-setting at the level of truth and impact frames, four videos already had a negative emotional bias towards the presentation of facts, focusing on the presentation of negative information. At the action frame level, the choice was made not to provide future advice or to provide adaptive advice that would not fully change the status quo.

Whether the agenda is set at each level of framing depends on the choice of content and the expression of the media's affective tendencies. Different media agenda-setting will also achieve different public agenda effects.

7.3. Analysis of public agenda side

In terms of the impact of media frames on audience perceptions, i.e. the “framing effect”, Entman argues that frames can generate as much power as language itself. “Framing resonance effectiveness is closely related to framing effect, a concept related to the power of framing, i.e. the potential of frames to elicit audience reception of core ideas, cause and effect relationships, value judgments, solutions, etc. The concept of framing effect is also related to the power of framing to influence audience perception. [8]

7.3.1. Content attributes in the first and second levels of the public agenda

7.3.1.1. Issue summary

By inputting the documents generated by the MDCOR into SENA, the team got their first batch of results.

The official channel is separated into two topics. Based on generalization manually of the most representative comments generated, topic 1 can be identified as "Beneficial and harmful implications of AI in education"; Topic 2 can be identified as "Discussions on potential dangers and threats of AI in education". Overall, the two different channels have shown a heated debate regarding the future development of AI, with a clear discrepancy between positive attitudes and negative attitudes.

The personal channel is separated into four topics. By implementing the same generalization method as the official channel, the four topics are identified as: topic 1 "AI impact and capabilities on future jobs"; topic 2 "Support and oppose of AI ethical standpoint"; topic 3 "Purposes of AI"; topic 4 "Pros and cons of AI for reading and writing"

Despite the differences, the two channels have some similarities. All the six topics (2 official and 4 personal) show a trend of positive sentiments outweighing negative sentiments. Not only is "positive" outweighing other sentiments, "anticipation", "joy", "surprise", and "trust" all received higher scores than the negative sentiments.

Comment threads under official and self-published videos have their own commonalities. There are similarities in terms of thematic content and emotional attitudes.

7.3.1.2. Word cloud comparisons

In the first level of agenda setting, i.e. object agenda setting, the keywords in the user comments basically match the main content of the media video. It can be seen that the medium largely determines the audience's perspective.

In the word clouds of the official channel, Topic 1 and Topic 2 actually have extremely similar usage of words. The only difference shown on the word cloud is the frequency of words used. As the two word clouds represent, the most frequent words and themes differ from each other. In the word cloud of the official channel, some of the words with highest frequency are "good", "student", "china", while on the side of the word cloud, more specific words such as "learn", "privacy", "future", "scary", "control", "bad" appeared.

In the word clouds of the personal channel, the four topics show a more intense and more diversified word than those of the official channel. With the same algorithm applied, the word clouds are inundated with more words. The ones with the most frequencies are "good", "write", "think", "chatgpt", "learn". Others include "human", "use", "people".

It is worth noting that the video content posted by self-published bloggers is more dispersed due to the low tightness of the content around the main topic compared to the official medium. This agenda-setting feature also has an impact on the subject matter of user comments, as reflected by the high frequency of small words in the word clouds of individual channels.

Overall, in the first level of agenda setting, i.e., object agenda setting, the keywords in the user comments basically match the main content of the media video. It can be seen that the medium determines the audience's perspective to a large extent. Meanwhile, there are still some differences between the keywords in the user comments and the main content of the media video.

The influence of media frames on people's public opinion varies according to their familiarity with the relevant issues, while the deviation between media reports and audience's daily experience, including the degree of audience's interest in the reports, traditional religious and political concepts, the deviation of cultural dimensions, and the audience's daily communication and habits, are also factors affecting the role of the traditional framing effect. Users' personal cognitive structure carries certain biases and stereotypes, which to a certain extent can cause the bias of agenda-setting results.[28]

7.3.2. Sentimental attributes in the second level of the public agenda

Emotion is a major factor in framing influencing audience perceptions [28] Is there such a correlation between the narrative emotional coloring of short videos and the emotional coloring presented by comments? How does agenda setting at the level of emotional attributes of the medium affect the emotional coloring of comments?

7.3.2.1. Overall sentimental categories of comments

Through sentiment histogram comparisons, the overall trend of the sentimental color of the individual comment threads in the official and personal channels is of similarity. Positivity, trust, and anticipation are high, anger, disgust, negativity, and sadness are low, and other sentiment values are in the middle. This is understandable. Even though the topics of comments on official and personal channels are different, they all center around “the potential impact of the use of AI technology in education on the future”, which means that based on the same factual background, even though the official media and personal media chose different topics and tendencies to report on them, they both conducted their reports in the Real frame and the Impact frame. This means that even though the official media and personal media chose different topics and tendencies, they both set the agenda in the Real frame and Impact frame, i.e., the video content shows the current situation and impact of the “use of AI technology in the education sector”. Based on the presentation of objective facts, there is a convergence in the emotional response of the audience.

Meanwhile, in the five frames of Real frame, Hoax frame, Cause frame, Impact frame and Action frame, the official media and self-media channels have made a lot of comments on AI technology in education., the trade-off between official media and personnel channels on whether to set the agenda or not, as well as the difference in the way of agenda setting, cause the difference in the emotion histogram.

7.3.2.2. Sentiment categories of comments in different types of media

Comparison of sentiment histograms

Official channel: “Positive” and “trust” overweight the others

As can be seen from the sentiment histogram, in the official channel, no matter V1 or V2, two sentiments stand out: “positive” and “trust”. The appearance of the two sentiments can be justifiable, as the news released in the official channel are trustworthy, and people are interpreting the “AI in education” topic in a positive way. In both of the graphs, the sentiment that ranked the third is “anticipation”. Based on this sentiment, it can be interpreted that as the official channels such as official news websites and organizations that are in close cooperation with the AI companies portray about the upcoming fusion of AI in education, the audience heard it for the first time. Therefore, feelings of anticipation can be created. Besides anticipation, “joy” and “surprise” ranked the fourth and the fifth in the histogram. Their generation shares similar mechanisms with “anticipation”, as they come from the official announcements. Yet, “negative” and “fear” are present with similar levels. However, they are far lower than “positive” and “trust”. Additionally, sentiments such as “anger”, “disgust”, and “sadness” are all way fewer than the positive sentiments. In the case of official channels, there are far lower negative sentiments than positive sentiments, indicating an overall positive trend of both topics.

When comparing topic 1 to topic 2, topic 2 has high scores for every sentiment. This means that regarding the topic of potential threats and dangers, the audience are more emotion-intensive. “fear” and “negative” appear in topic 2 with a bigger percentage of the overall sentiments. This is justifiable, due to the key words “threat” and “danger” mentioned in the generalization of topic 2.

Personal channel: Lower “trust”, higher positive attitude

The personal channel sentiment histograms show different trends at small details with the official channel. Firstly, “positive” sentiment conspicuously outperforms “trust”. This can be justified by the difference of channels. The personal channels comprise influencers and small organizations that are not officially certified. The audiences’ trust toward these channels will be lower, as they are not certified and trustworthy. Nevertheless, the two sentiments still ranked the first and the second in the histogram, indicating an overall positive trend. The third and the fourth rank are still “anticipation” and “joy”, similar to those of the official channel. Noteworthy, the level of these two sentiments varied among topics. Topic 1, 3, 4 share a higher rate of these two sentiments, while topic 2 has lower. This is justifiable due to the key word “ethical standpoint” in topic 2. This shows that people are aware of the AI standpoint, and have less expectation of it being ethical.

While positive sentiments still take account of most of the trend, negative sentiments do take their own portion. A notable point is that “fear” and “sadness” varies between topics too. “sadness” in topic 3 is higher than the other three topics, indicating people’s pessimism regarding the ethical standpoint. Furthermore, the level of “anger” and “disgust” in topic 1,3,4 are substantially higher than that in topic 2 because topic 1,3,4 are all considering the pros and cons. This will engender sentiments of both sides.

Word Cloud Comparisons

Also, this difference in detail is reflected in the word cloud map.

Official Channel: Positive trend with diversified adjectives

on the side of the official channel word cloud, more specific words such as “learn”, “privacy”, “future”, “scary”, “control”, “bad” appeared. These words are mainly theme-related or emotional words. Overall, the word clouds show a positive trend, combined with further adjectives expressing both positive and negative opinions regarding the topic.

Personal Channel: More intense and diversified emotions

In the word clouds of the personal channel, noteworthy, there are more emotional, or descriptive, words appearing, such as “danger”, “many”, “problem”, “everything”, “true”, “end”, “little”, “great”, “replace”, “love”. This shows a more diversified emotions discussed in the personal channel than the official channel.

Overall, when comparing the official channel and personal channel together, several comparisons can be made, juxtaposing with justifiable interpretations.

The two channels have some differences. Firstly, the official channel contains a higher level of trust than the personal channels. This is due to the characteristics of channels: Audiences are more likely to believe the information posted in official news and organizations. Secondly, in the form of ratio, the official channel has a higher level of negative sentiments, such as “fear”, “anger”, “disgust”, and overall “negative”, while the personal channel has a lower percentage of those.

Self-media videos often deviate from the central theme, resulting in fragmented content. This fragmentation in videos leads to a disjointed emotional attribute agenda-setting, which in turn creates numerous subtle variations in public opinion.

Social movement scholars David Snow and Robert Benford have identified four interrelated factors that influence the efficacy of frame resonance: empirical credibility, experiential commensurability, These are empirical credibility, experiential commensurability, ideational centrality, and narrative fidelity. They refer to the credibility of the framer, the extent to which the frame matches the evidence, the proximity of the framed content to the lived situation, and the importance of the ideas promoted in the frame in the minds of the audience, The relevance of the frames to the existing culture (including myths, beliefs, etc.). The official media has higher credibility due to its characteristics such as rigor and professionalism, and the agenda-setting content of the official media has a higher degree of credibility for the audience. Self-media, on the other hand, is an open mode of news production, with audience participation and diverse modes of expression. The public is the primary frame provider of self-media, and through the interactive use of a variety of symbols, its texts are characterized by popularity and fun. [8]Self-media are easily influenced by profit goals, audience polarization, and their own positioning, and report more on marginal information that is weakly related to the event, which leads to the deviation of topic selection and biased agenda setting. [32]

8. Conclusion

In conclusion, the findings of this research underscore the critical difference between the voices of channels on YouTube, highlighting its implications for Generative AI's contributions to the educational field and paving the way for future exploration and understanding. During the research process, the researchers went through the process of discussing the topic and ways of investigation, collecting data and defining the ones with the most comments, using tools such as MDCOR and SENA to analyze the data and comparing the dataset with the group discussion. For instance, agenda setting was widely used during the research: how media shapes reality and selectively reflects the audience. The theory is divided into two steps: traditional agenda-setting and attribute agenda-setting.

Key findings from the study are revealed regarding the various topics and emotional tenor conveyed, depending on the content source, in YouTube comments regarding artificial intelligence in education. Official channels typically portray AI in a more controlled and positive light because they are frequently associated with respectable news organizations and academic institutions. Positive sentiment and trust are prevalent in the comments on these sites, which is indicative of this. These channels' material frequently highlights the advantages and possibilities that artificial intelligence offers the educational sector, with a particular emphasis on individualized learning and increasing teaching effectiveness.

On the other hand, a broader spectrum of opinions may be seen in the video comments left by users or influencer channels. These publications frequently discuss the advantages and disadvantages of using AI in the classroom. These responses had a wider range of emotions, including increased fear, skepticism, worries about privacy, and ethical ramifications. This range of emotional reactions highlights how viewers are engaging more critically with material across channels, which may represent a more broad and unfiltered range of viewpoints.

The study's conclusions demonstrate how crucial the media is in influencing public opinion. According to the media agenda-setting hypothesis, public opinions about certain problems are influenced by the focus that various media outlets place on them. Our research supports this hypothesis by demonstrating that, whereas personal media platforms offer a more critical and nuanced viewpoint, official media frequently highlights the advantages of artificial intelligence in education. This variation in how different media portrayals impact the feelings and viewpoints of their individual audiences emphasizes how important the media is in shaping public conversation and determining its agenda.

9. Limitations

The number of samples selected in this paper is insufficient: there are fewer video works on YOUTUBE platform about "AI Application in Education", and the number of related comments is small, so after eliminating invalid information such as low relevance and duplicated content, the number of valid samples obtained is slightly smaller. Therefore, the content framework, video framework, emotional color and so on are not universally applicable, which to a certain extent causes some errors in the research results.[35]

Because media coverage does not always have an immediate effect, time lags are crucial to understanding how media influence develops over time. A media intervention may have a delayed effect, with early exposure resulting in alterations in public views and behavior that become apparent later. This study overlooks how the timing of media coverage influences agenda-setting efficacy by not accounting for the temporal dimension of media influence. For instance, a matter that first captures the interest of the media may gain significance over time, or the influence of continuous media exposure may change as the matter continues to be in the public's focus. Disregarding these temporal delays hampers the study's capacity to comprehensively grasp the functioning of media influence over varying time intervals.

This study ignores the possibility of intermedia agenda setting and its implications. There are complex connections between OFFICIAL MEDIA and WE MEDIA. Together, they have an impact on the public opinion environment.

Category construction in agenda-setting research carries certain risks. Even though this study compared and analyzed the methods of category construction in domestic and international academic circles, it chose the most suitable construction method for the topic of "AI Application in Education". However, when the framework is used as the basis for category construction, the result may be a false correlation when news and opinions on these different topics are mixed under the same framework.[36]

The analysis of the content framework, visual framework, emotional framework, etc. only stays at the level of content analysis, lacks the support of rigorous data analysis, and has a certain degree of subjectivity.

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