Exploring User Engagement in Political YouTube News: A Study on BBC Breaking News

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Abstract

This study explores the negativity bias in user engagement with YouTube news and the effectiveness of negative sentiment in attracting attention. I investigate the difference in user engagement, specifically in the form of comments and likes, between political and non-political news. The paper explores whether political news attracts a higher quantity of negative sentiment comments and examines the differences in likes given to negative comments in both political and non-political news. The findings reveal a stronger negativity bias in user comments on political news, while relatively fewer likes are distributed to negative comments in this category. This paper is based on analyzing comments and likes from BBC Breaking News videos.

Keywords: Social media, User engagement.

Declaration Large Language Model (OpenAI 2024) is used in the research process for grammatical correction, refining writing and idea of the criteria to categorise political and non-political news, debugging and writing annotation for the code. The Large

Language model does not provide any of the collected data.

1 Introduction

Over the past few decades, social media platforms have became a significant source of news. Exploring user engagement with social media news offers insights to how audiences allocate their attention and expression their opinion during news consumption of different types. User engagement with political news, in particular, can vary significantly compared to other topics, as audience reactions are often shaped by individual opinions and ideological leanings. This paper aims to explore user responses in political news, with a specific focus on the BBC YouTube channel, providing a preliminary analysis of the nature of these interactions.

The finding provides evidence to support the hypothesis that political news attract more negative sentiment in user comments. However, this is likely not the result of negativity bias among all viewers, but could be the result of computer-mediated communication (Ho & McLeod 2008). Negative comments on political news tend to receive fewer likes, suggesting the overall audience of the video does not share a similar trend in opinion and sentiment towards the same topic.

Numerous studies of different fields have explored the effectiveness of social media in understanding user engagement in political communication, with most of the research focusing on platforms such as Twitter and Facebook. As a video-sharing platform, YouTube's user engagement tends to be more focused, with interactions primarily centered around the specific content of the video. As a result, the discussion environment is heavily shaped by the category of the video, leading to topic-specific user engagement.

Robertson et al. (2023) studied the impact of negativity bias on user engagement, discovering that the presence of negative or emotionally charged words in news headlines increases click-through rates for online news websites. While their study also examine how user engagement is influenced by negativity bias, it is dedicated to online news platforms, using views to measure user engagment. My research focuses more on how news topic influence user engagement and affect the discussion, while using comment and likes distributed to comment to study user engagement in user generated content with a given topic.

(Stieglitz & Dang-Xuan 2013) reveal the connection between sentiment and online engagement in terms of political news in terms of total sentiment, showing that stronger sentiment also attracts more retweets and receives retweets more quickly in terms of Twitter postings in political communication. This research focus on a similar question in the form of video, whereas the likes distributed to comment of the topic, equivalent to the response to retweets, are considered to examine the difference in discussion environment and engagement, while the main topic does not exhibit strong sentiment on a topic.

Furthermore, Westerwick Axel (2017) shows how the framing effect of news influences the user, as users selectively expose themselves to attitude-consistence messages for a longer period and quantity, and the interaction, including comments received by social media posting, are also consistency to the original posting (Bagic Babac 2022). This similar result potentially allow us to associate the sentiment of comment to potential opinion on standings hold by the given viewers on the topic, providing theoretical support of the bias in user engagement.

Khan (2017) investigate the nature of user engagament in YouTube, and discovered that seeking social interaction have the stronger relationship with commenting, while comment is also driven by many other predictors including seeking information(by asking questions or starting discussions). Seeking information and entertainment are highly significant estimator of video and comment consumptions, which can potentially create a difference between audience that comments and those that view comments and videos. Similar mechanisms are also modelled in Guriev et al. (2023), which identify persuasion, partisan signaling, and reputation concerns as drivers of content sharing in Twitter.

Aridor et al. (2024) provided an overview of economics research in social media, discussing the non-monetary incentives of social media content production(commenting) and consumption(viewing videos and comments), providing the basis for our analysis.

By focusing on YouTube, I explore the effect of negativity bias have on user engagment in political news. This research contributes to the existing bodies of research on user engagement in social media, focusing on how commenting and liking behavior differs between political and non-political topics. Additionally, by examining the influence of video topics on user sentiment, this research provides empirical evidence of negativity bias in political news in commenting, which is not representative of the overall opinion of audience.

2 Theoretical framework

If biases of online news (Robertson et al. 2023) exist in video-based news, political news would be expected to attract users with a negativity bias, and the comment distribution in political news would be skewed, with negative comments receiving a higher proportion of the numbers and likes received.

Users with negative bias against a piece of news are more likely to view the news due to negativity bias (Stieglitz & Dang-Xuan 2013), and combined with the natural difference between the type of user interaction (Khan 2017), leading to a skewed distribution of viewers, introducing a potential bias while using social media news engagement to evaluate political opinions.

2.1 Assumptions

To ensure the validity of the regression analysis, I adopted the Classical Linear Regression Model (CLRM).

Furthermore, I also have the following assumption on the data collected.

- **YouTube Suggestion:** The two category of news is presented to viewers equally.
- **Viewer Preferences:** The viewers of political and non-political news are from the same population.
- **Liking behavior:** Viewer only likes comment that have similar opinions to their own, or have the same sentiment towards the video.

2.2 Hypotheses

Based on the theoretical framework, I propose two hypotheses regarding user engagement and interaction with political and non-political news

Hypothesis 1 (H1) *Political news attracts a higher proportion and volume of negative sentiment comments compared to non-political news.*

This hypothesis examines whether political news elicits a greater proportion of negative sentiment comments than non-political news, suggesting the presence of a negativity bias. It also considers the overall quantity of negative comments, while controlling for other variables.

Hypothesis 2 (H2) *Likes are more likely to be distributed to negative sentiment comments in political news compared to non-political news.*

This hypothesis would test the number of likes received by negative sentiment comments. The result would reveal whether whether political news viewers are more attracted to negative comments.

3 Research Method

3.1 variables

3.1.1 Variable of interest

The variable of interest in H1 is the proportion and number of negative comments for political and non-political news, measuring the difference in user interaction between the two categories. This variable provides an interpretation of user engagement and measures the potential negativity bias in user responses based on sentiment.

In H2, the variable of interest is the number of likes received by negative comments in political and non-political news. This evaluation intends to provide an overview of the effectiveness of certain sentiments in engagement-seeking under the given discussion environment (political and non-political categories).

3.1.2 Control variable

An overview of the control variables is provided in table 1.

To determine the category of the video, I created criteria that include news topics considered political news in this research, as provided in Appendix A.

Table 1: Control variables

Coefficient	Description	Control
Date	Date when data is collected.	July 9th 2024
Playlist of videos	YouTube playlist of selected videos.	BBC breaking news playlist.
Category of the video	Political and non-political category of the videos	Manually categorised with a detailed criteria.
Number of comments	The total number of comments of videos	Controlled to eliminate outlier when appropriate, depending on distribution.
Number of views	The total number of views of videos	Controlled to eliminate outlier, depending on distribution.

The category of the video, the number of comments, and the number of views are the explanatory variables.

3.2 Research Design

To test the hypothesis, I will be collecting comment-related data of political and non-political news to explore the potential differences in their distribution, and analyzing the effectiveness of user engagement of different sentiments to investigate the potential bias in YouTube news of different categories.

To do so, the number of negative, positive and neutral comments would be collected to analyze the proportion of comments for news of the two categories, which would be tested directly to uncover the difference in user interaction under the two categories.

Furthermore, the effectiveness of such comments would be evaluated by comparing statistics related to likes received by comments of different sentiments under the given news category, potentially uncovering how other users react to the comment and providing a further view of user engagement under YouTube news.

3.3 Empirical Framework

3.3.1 Hypotheses 1:Analysis of difference in negative comment

I considered a model with two categories, with the number of total comment being the main explanatory variable for number of negative comments, implying the number of viewers with an opinion to comment.

Then, the model would consider political and non-political category of each news video individually, which represent the group of topics this research plan to explore, represented by a dummy variable $category$, defined as 0 for non-political news and 1 for political news.

As the number of negative comments($negative$) is associated with number of total comments($comment$), the framework hypothesised that political news would attract biased comments as a proportion of negative comments, hence the analysis focus on the interaction effect, providing a basic model:

$$\begin{aligned}\ln(negative_i) = \alpha_0 + \alpha_1 \ln(comment_i) + \alpha_2 \ln(views) \\ + \alpha_3 category_i + \epsilon_i\end{aligned} \tag{1}$$

The decision to apply a logarithmic transformation to all numerical variables was based on the observed distribution patterns in the data. Specifically, many of the variables exhibited substantial variation between values, making it difficult to capture meaningful trends using the original scale. Furthermore, certain observations were expected to have disproportionately higher values, leading to skewed distributions. Finally, the political category is expected to have a proportional influence on the total number of negative comments and likes received by negative comments, hence taking logs would allow the coefficient for the dummy variable $category$ to be expressed as an proportional change of dependent variable. By taking the log of these variables, the data were normalized, reducing the influence of extreme values and making relationships between variables more linear, which enhances the interpretability of the analysis.

3.3.2 Hypothesis 2:Evaluting the effectiveness of likes attracting under different category

In the model of total number of likes distributed to negative comments under different categories, I used the number of views, negative comment and video category as explanatory variables, taking log to the numerical variables display the potential difference in the proportion of audience holding negative opinion on the topic and exhibiting negativity bias.

$$\ln(likes_i) = \beta_0 + \beta_1 \ln(negative_i) + \beta_2 \ln(views_i) + \beta_3 category_i + \epsilon_i \quad (2)$$

Where $negative_i$ is the total number of negative comment in video i, $likes$ is the number of likes received by negative comment and $views$ is number of views of the video.

The total number of negative comments is dependent on the category tested in the first hypothesis, thus there could exist and endogeneity problem, and I decided to use the model in the first part as the first stage regression, which would allow me to use a two-stage least square approach to the second hypothesis as provided below.

$$\ln(\widehat{likes}_i) = b_0 + b_1 \ln(\widehat{negative}_i) + b_2 \ln(views_i) + b_3 category_i + \epsilon_i \quad (3)$$

In this new model, the $\ln(\widehat{negative}_i)$ is the prediction using $\ln(comment_i)$, $category_i$ and $\ln(views_i)$, using a estimation of model 1, to handle the endogneity problem between negative comment and total comment.

3.3.3 Mediation analysis

To better understand the relation between the variables, I created the figure below in figure 1 revealing the hypothesised connection between the variables.

I intend to use mediation analysis to separate the effects of negative comment, this allow us to better reveal the causal effect and chain by which total comment is able to influence the numbers of likes received by negative comments, providing a better understanding over the causal implication between variables.

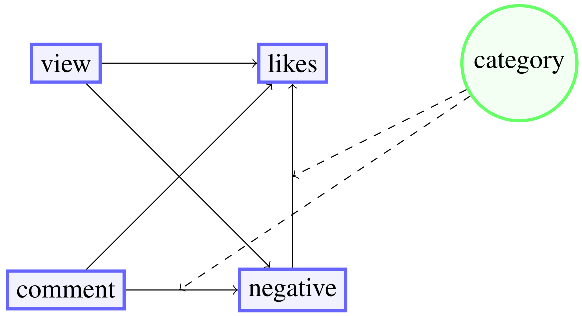


Figure 1: Relation Graphs of Variables

3.4 Data collection methods

This study uses data collected from the Breaking News playlist on the YouTube BBC channel as of July 9th, 2024, consisting of a sample of 400 YouTube news videos published between April 2023 and July 7th, 2024. A total of 393 videos were open to comments and collected for analysis. The data was accessed through Google's Data v3 API via an automated process using Python. The dataset provides an overall view of sentiment distribution and its impact on user engagement in this particular news source.

The video-level data includes the video ID (vid), publication date, number of views, and title. The comment-level data includes the number of likes received, and the corresponding sentiment of each comment is computed before analysis. No personal information is collected, and the comments are only analyzed for sentiment after being accessed via the API.

Additionally, the likes received by comments will be analyzed to evaluate the effectiveness of sentiment in attracting engagement and to further explore how sentiment influences engagement in political versus non-political videos.

3.5 Data Analysis Methods

The sentiment analysis is based on the model developed in (Hartmann et al. 2021). This model classifies the pre-processed comments into three classes: positive, negative, and neutral. In the data cleaning process, I removed any non-alphabetical and irrelevant information, including emojis, special characters, and external links. To ensure that the comments are in English, those with a diacritic proportion higher than 0.05 or containing non-alphabetical characters were dropped. The cleaned comments were then tokenized using the tokenizer provided with the model, which predicts the category by assigning a sentiment score.

The proportion of negative comments is hypothesised to follow a beta distribution, hence will be tested using a Kolmogorov–Smirnov test to assess the overall difference between the two distributions, which allow the test for this distribution, but might lack power due to its non-parametric nature. The proportion of negative comments for political and non-political news will be compared, against the alternative hypothesis that the distribution of negative comments for political news lies below that of non-political news, indicating that political news has a higher proportion of negative comments.

Furthermore, I intend to design specific models to understand the quantitative relationship between the political category of news, the number of negative comments, and the likes received by these comments, which will serve as the main tools for testing the second hypothesis.

3.6 Ethical Considerations

To protect the privacy of users, no user data is collected during the data collection process, and raw comments will not be provided by this research to prevent disruption to the YouTube online community or any individual users, as well as to prevent the possibility of identifying individual users through comments. Furthermore, the data collection and analysis are carried out through an automated process, ensuring that no comment data is accessed by the researchers individually, nor is it traceable to the original comment.

However, the summary statistics, video-level data, and replication kit will be provided to ensure the replicability and transparency of this research.

4 Data

4.1 Descriptive statistics

The data is collected from 397 videos. With 270 political and 123 non-political news, with the number of views spanning from 11091 to 9832056 views.

I removed any outliers that are 1.96 standard deviations away from the mean after taking the natural log. However, none of the observation were removed before introducing the $likes$ variable, which is the total number of likes receieved by negative comments for the video. To ensure the consistency of the two model, I also used $likes$ to control for outliers, removing 22 observation leaving the sample size of 371, with 110 being non-political and 261 political news.

A summary statistics is provided in table 2 the explanatory variables.

Table 2: Summary statistics for control variables

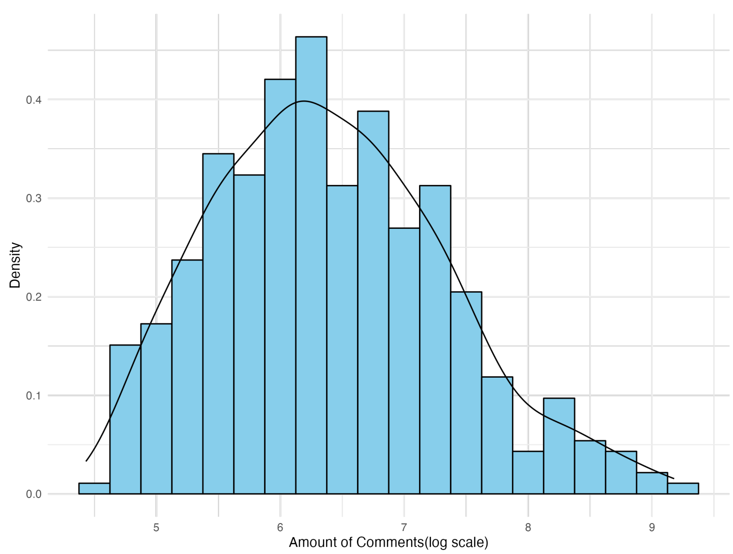
Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Number of comments	84.0	295.0	551.0	977.9	1148.5	9686
Number of views	23209	97314	179809	389010	381052	9832056

I also conducted the Jarque Bera normality test, with result shown in table 3. For the variables mentioned above, as the data appears to be negatively skewed displayed in the summary statistics and considering the nature of YouTube videos, I used log scale for both of the variables to test whether if they follow log-normal distributions.

The comments count would contribute to the variable of interest directly in hypothesis one, and would influence the number of likes with negative comment as a mediator, thus I am interested in its distribution, displayed in the histogram and density plot in Figure 2.

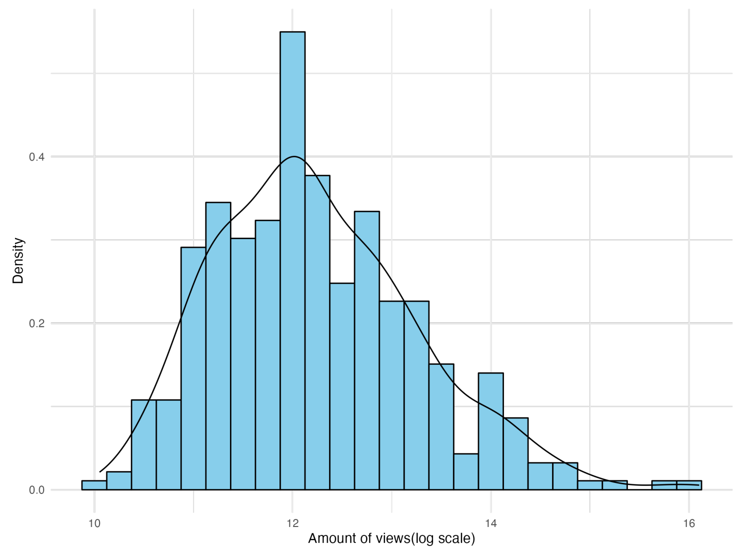
Table 3: Jarque-Bera test results for control variables

Variable (ln scale)	Test Statistic (X-squared)	p-value
Number of views	23.463***	<0.001
Number of comments	10.727**	0.004684
Number of negative comments	9.8688**	0.007195



Note: The histogram is provided with the bin of 0.25

Figure 2: Distribution of log number of comments for videos



Note: The histogram is provided with the bin of 0.25

Figure 3: Distribution of log views for videos

To test the assumptions, I used Kolmogorov-Smirnov test on the number of comment and views, with detailed result presented in appendices D.1, and found that there is no significant evidence that the total number of comment is difference between political and non-political news, indicating that the two videos does not have significant difference in overall user engagement. However, the non-political videos tends to have more views compared to political videos, and could potentially lead to biased result.

This result indicates that viewers of political news are more likely to comment on the video compared to non-political viewers, leading to a similar number of comments despite having fewer views. Considering the incentives for generating content (Aridor et al. 2024). (Guriev et al. 2023) provided a model of user engagement in terms of content sharing driven by persuasion, partisan signaling, and reputation concerns, potentially explaining why political news have similar distribution of comments despite lower views.

4.2 CLRM Assumption

To test for Collinearity, I calculated the variance inflation factor for all of the variables in table 4, and also ran a basic linear regression on the views of the video and the number of negative comments in table 11.

Table 4: Variance inflation factor for model variables

$\ln$(Negative)	$\ln$(Views)	$\ln$(Comments)
31.80	4.07	43.37

In regression displayed in table 11 in appendix B, the Multiple R^2 is only 0.5818 and Adjusted R^2 being 0.5807, which is moderate and acceptable, thus I would continue using $views$ as an explanatory variable in model 3.

However, as the VIF showed linearity between number of negative comment and total comment, thus I omitted the total comment in the model 3, as it would introduce colinearity and reduce the effective of the model.

To avoid endogeneity problem between number of negative and total comments, I will use $\widehat{negative}$ as a instrument approximated from model 1, since the endogeneity between $negative$ and $comment$ would lead to biased estimators.

To test whether if total comment is endogenous to model 3, I conducted a Wu-Hausman test for endogeneity and a Weak instrument test on $negative$, with the result displayed in table 12 in appendix B. This result showed the effectiveness of this $\widehat{negative}$ variable at ¡0.001%. However, the Wu-Hausman appears to be marginally significant, indicating a potential issue of endogeneity and of incorrect functional form, which should be taken into account in further exploration.

I also used a Ramsey RESET test to assess whether a linear function is appropriate for the model. The test was not significant at the 5% level for both model 1 and model 3, as shown in Appendix B, under Table 13. This indicates no significant evidence of an inappropriate functional form at the 5% significance level, allowing us to use a linear model for approximation.

Both models exhibit homoscedasticity in their residuals, as tested using the Breusch-Pagan test in Table 14, at the 5% significance level.

However, the residuals do not follow a normal distribution, as tested through the Jarque-Bera test shown in Table 15. Thus, this data set does not satisfy a classical normal linear regression model (CNLRM) (Gujarati 2019), which could lead to biased estimates and significance levels in the regression results.

5 Findings

5.1 Hypotheses 1:Analysis of difference in negative comment

5.1.1 Proportion of negative comment

Since I am interested in the proportion of negative comments in this research, which lies in the range $[0, 1]$. I hypothesize that the distribution would follows a beta distribution due to the proportional nature of the data.

Therefore, I used the Kolmogorov–Smirnov test, as shown in Table 5, to test the distribution of the proportion of negative comments for both the political and non-political categories. At the 0.05 significance level, we are unable to reject the null hypothesis that the proportion follows a beta distribution.

Table 5: KS-test result for proportion of negative comment for beta distribution

Category	test statistics(D)	p-value
Political news	0.056929	0.3661
Non-political news	0.047652	0.9641

I am interested in understanding the difference in negative comment proportion distribution between different categories of news. To do so, I utilised a two-sample Kolmogorov-Smirnov test, with the alternative hypothesis that the CDF of political news lies under non-political news, meaning that a larger percentage of political news has a high proportion of negative comments. The result of the two sample Kolmogorov-Smirnov test is provided in Table 6, with the Empirical Cumulative Distribution Function(ECDF) provided in Figure 4.

Table 6: Two-sample Kolmogorov-Smirnov for proportion of negative comments

D^-	p-value
0.28199***	<0.001

Note:*,**,*** denote 5%, 1%, and 0.1% significant level, respectively.

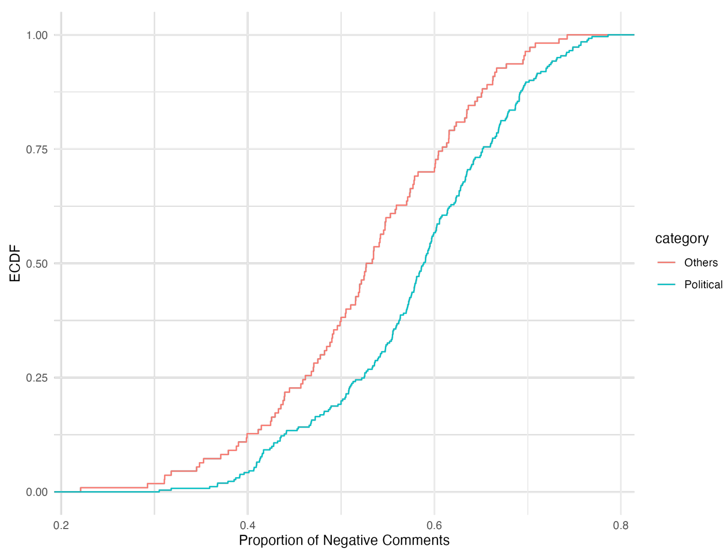


Figure 4: ECDF for proportion of negative comment by category

This test showed the political news has a higher proportion of negative comments in comparison to other comments, providing evidence for hypothesis 1 of this research. From this result, the higher proportion of negative comments indicates a difference in distribution between users who leave comments for political and non-political news, with political news more likely to be negativity-biased.

5.1.2 Number of negative comment

To quantify the proportional effect of the news category on the total number of comments, I employed an ordinary least squares regression analysis, as detailed in model 1. Additional statistics from this regression analysis are presented in Table 7.

Table 7: Multiple regression table for numbers of negative comments

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	0.3040	0.1239	2.453*	0.01461
$\ln(comment)$	1.1570	0.0175	66.181***	<0.001
category	0.06234	0.02053	3.036**	0.00257
$\ln(views)$	-0.1588	0.01627	-9.759***	<0.001

Note: *, **, *** denote 5%, 1%, and 0.1% significance levels, respectively.

The regression analysis reveals strong model performance, with a multiple R^2 of 0.9697 and an adjusted R^2 of 0.9695, indicating that the model explains a significant portion of the variance in the total number of comments. The F-statistic for the regression is 4036, with a p-value of less than 0.001, suggesting that the model is statistically significant.

In this model, the category of news demonstrated a significant proportional effect on the number of negative comments, measured in logarithmic form. From the regression analysis, I expect the number of negative comments in political news to be 6.234% higher than that in non-political news. Furthermore, since there is no significant difference in the mean number of comments between political and non-political news, it is unlikely that this result is due to a difference in user engagement between these two types of news.

However, negative correlation is reviewed between number of views and negative comment, consistent with the preivous Kolmogorov–Smirnov test, showing that political news have less views compared to political news.

I found significant evidence for the difference in the number of negative comments.

Furthermore, I also explored the connection between neutral and positive comments with political content through a multiplicative dummy variable, provided in appendix C. I found no significant effect on positive comments, however, there are significant interaction effects on neutral comments which decrease the number of neutral comments by 7.41%, meaning that the increase in negative comments is likely at the expense of neutral comments.

The regression analysis provides evidence that users engaging with political comments exhibit a negativity bias regarding the topic, compared to non-political news, thereby revealing more about online commenting behavior.

Overall, there is significant evidence that political news has a higher proportion of negative comments and is associated with increase in the total number of negative comments relative to non-political news, which can potentially be evidence for the skewed user engagement in political news due to negativity bias.

5.2 Hypothesis 2:Evaluating the effectiveness of likes attracting under different category

To test the effectiveness of likes in attracting comments of different sentiments, I utilized video-level data on the likes received by comments with a given sentiment. This approach was preferred because micro-data would share the same variables for views and the number of comments, leading to significant variability within the same video.

In this research, I am interested in the proportional effect of the news category on the number of likes received by a comment. Therefore, I applied a logarithmic transformation to all numerical explanatory variables as well as the dependent variable due to their large variations.

The results from Hypothesis 1 may indicate a negativity bias in commenting rather than a negativity bias among viewers overall. Since the category alone does not directly influence the number of negative comments, I conducted another regression that replaced the views variable with the total number of negative comments. This new regression allows for a deeper understanding of how news categories can influence user engagement.

Table 8: Multiple regression table on negative comment likes

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	0.33197	0.37621	0.882	0.3781
$\ln(\widehat{negative})$	1.06973	0.04628	23.117***	<0.001
category	-0.26065	0.06371	-4.092***	<0.001
$\ln(views)$	0.07792	0.04329	1.800.	0.0727

Note: *, **, *** denote 5%, 1%, and 0.1% significance levels, respectively.

The model has a residual standard error of 0.533 on 367 degrees of freedom, with a Wald test statistic of 505.3 on 3 and 367 degrees of freedom, significant at the 0.1% level.

In this regression, the effect of video views is only marginally significant, suggesting that the impact of views might not directly translate into the number of likes received by negative comments. Instead, this effect may be reflected in variables such as the number of negative comments, which is influenced by the total number of views.

However, the effect does not exist for positive and neutral comments, with details provided in appendix E. The political category does not display a significant effect on the likes received by neutral and positive comments, indicating a potential disconnect.

The regression reveals a negative coefficient for the political category, suggesting that political news actually reduces the number of likes given to negative comments, with an estimated decrease of 26.06% when the news is political. This contradicts the original hypothesis and theoretical framework, and may reveal differences in social media engagement regarding likes and comments. It shows that users with negative opinions are more likely to leave comments compared to others, while the news itself attracts more users with similar attitudes who tend to react to pro-attitudinal comments.

5.3 Mediation Analysis

To better understand the effect shown in model 3, I conducted a Mediation Analysis, with the intention to understand the quantitative effect of treatment variable $comment$ on the mediator variable $negative$, holding $views$ and $catorgy$ as control, and evaluated their effect of the dependent variable $likes$. The direct effect of $comment$ would allow us to understand whether if $comment$ is an appropriate variable to understand user opinion. All variable has been taken log with the base of e.

In this analysis, I used model 1 as the meditation model, and used the model 4 as the outcome model.

$$\begin{aligned} \ln(likes_i) = c_0 + c_1 \ln(negative_i) + c_2 \ln(views_i) \\ + c_3 \ln(comment_i) + c_4 category_i + \epsilon_i \end{aligned} \tag{4}$$

Where c_3 measures the direct effect of log comment on log likes.

Nonparametric bootstrap are used for the mediation analysis to generate the ECDF due to the non-normal nature of the number of negative likes identified earlier. I utilized the R package Tingley et al. (2014), with 2000 simulation producing the result in table 9.

Table 9: Causal Mediation Analysis Results: Nonparametric Bootstrap Confidence Intervals Using the Percentile Method.

Causal Mediation Analysis	**Estimate**	**95% CI Lower**	**95% CI Upper**	**p-value**
ACME	1.579	1.175	1.97***	<0.001
ADE	-0.348	-0.723	0.07	0.11
Total Effect	1.231	1.109	1.35***	<0.001
Prop. Mediated	1.282	0.941	1.60***	<0.001

Note: *, **, *** denote 5%, 1%, and 0.1% significance levels, respectively. Sample Size Used: 371; Simulations: 2000.

As shown in the result, the total number of comment($comment$) does have significant positive indirect effect to the total number of likes received by negative comment, transmitted through the mediator. However, the average main effect of comment is negative and close to marginally significant, showing a supression effect of total comment on the number of likes recevied by negative comment. The main effect statistics indicate a larger number of comment does reduce number of likes distributed to negative comment, given that the number of negative comment is constant.

The model showed inconsistent mediation of the number of total comment on the likes received by negative comment, there is no significant evidence to say that total comment does not impact negative comments likes directly. The result for likes received by negative comment is hence heavily dependent on the proportion of negative comment in the particular video, whereas increase in comment with other sentiment is not expected to reduce the number of likes through dilution or providing subsitutes for viewers, consistent with the likes recevied by neutral and positive comment result in appendix C.

Overall, the indirect effect of total comment is significant and shown how total comment can influence negative comment, hence leading to a larger number of likes.

6 Robustness Check

The models satisfies the basic assumptions of CLRM, which gives a unbiased estimation for the coefficients.

The sample of data is relatively large to apply the necessary statistical techniques, which provides robust result despite the non-normality of the residuals in model.]

Alternative forms of model also revealed similar pattern in the result.

An alternative model for hypothesis 1 without log transformation the data showed a significant coefficent of the interaction term for both category and total comment, as well as cateogory and views, showing a similar result as model 1, where news in the political cateogry have higher proportion of negative comment, shown in appendix F model 22.

By using model in equation 5 to estimate $negative$, I also conducted a instrumental variable regression using model 6 significant negative effect of category on the number of likes received by negative comment. Through an interaction term between $negative$ and $category$, with coefficent and diagnostic of the instrument provided in appendix F table 23, justifying the result.

As the number of likes received by negative comment may be dominated by a certain outliers, I also used the method of collecting the trimmed sum of negative comment likes, between the 10 and 90 percentile, and using the same model 3 for its analysis. The result is consistence with our findings, showing a significant impact of political news in reducing the number of likes recevied by negative comment, with the coeffcients and test provided in appendix F, table 24.

7 Discussion

From the result for hypothesis 1, I hypothesize that a proportion of users subscribe to BBC channel because as provides pro-attitudinal news and, and have already experienced effective polarization toward this news source (Levy 2021). As the total number of views increases, more users with diverse attitudes are exposed to the video, particularly those who are not subscribed to the channel or who hold differing opinions. Neutral comments may come from users exposed to mixed-attitudinal news, which can reduce polarization. These users, who are either not subscribed to the news channel or do not hold strong opinions on the topic, are therefore less likely to view or comment. In contrast, negative comments stem from users who perceive the news as counter-attitudinal. However, these users do not fully re-optimize their browsing behavior, making them more likely to leave negative comments due to negativity bias.

When considering the drivers of YouTube interaction, users who leave comments may hold different opinions from those who simply view them. Commenters are often interested in social interaction, while viewers may be more focused on extracting the information they need from the comments. Consequently, viewers might ignore negative sentiment comments, which do not necessarily provide useful information, and instead turn to neutral comments, which could be more informative and align better with their motivations for consuming content on YouTube, and would require further research to test.

7.1 Limitations

There are still various limitations to this research. The research focused on only one source of news(BBC) and might not apply to all online news channels. Furthermore, the comment sample might be biased as only English is kept to be analyzed in the comment. Furthermore, the exact time of the video publication is not controlled, and news consumption responds strongly to external shock (Levy 2021) and could influence the reliability of the result.

Furthermore, there can potentially be vital difference between online and actual new opinions, or between social media users with difference number of usage, as studied in (Allcott et al. 2020), thus bias could exist in the sampling of comments and should be taken into consideration and the assumption of Viewer preferences might not hold. Furthermore, the YouTube suggestion algorithm might not present political and non-political news to the same population of views, and the YouTube suggestion assumption may fail.

The marginally significant main effect in mediation analysis indicate that the total comment might not be a suitable instrument of $negative$, as the effect of $comment$ might be ignored, while not using it as instrument causes endogenity and colinearity with $negative$ and making the model biased, hence another instrumental variable might need to be identified for this analysis.

Using the simple sum as a measurement for the popularity of negative sentiment comments can be dominated by a small number of popular comment instead of reflecting the whole population, hence a better method should be considered, for instance the use of mean of trimmed data, or through alternative functional form of regression.

The sampling method could be biased towards a particular audience, and potentially over-present viewers in the UK.

Model 5, used for robustness check, failed in the Wu-Hausman test, hence there can be endogeneity in the variables of the model, largely influencing the effectiveness of the model and reliability of the estimator.

8 Conclusion

These findings suggest a potential negativity bias in the comment of political news, but does not exist in the viewers of such news. The results suggest that political news has a significant effect in attracting negative comments, and indicate a difference between user engagement in the form of likes and comments, which should be taken into consideration while using social media data to analyze public political opinion.

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Appendix A Political classification criteria

1. Political Decisions of Government
   (a) Legislation and lawmaking.
   (b) Executive orders and decrees.
   (c) Government actions and publication of initiatives.
2. Elections
   (a) Campaigns and election processes.
   (b) Results and analysis.
   (c) Political debates and candidate profiles.
3. Changes in Policies
4. Expression of political opinion
   (a) protests
   (b) strikes
5. International Relationships:
   (a) Diplomatic actions or visits
   (b) International conflicts and resolutions
6. Politician related
   (a) Official Statements
   (b) Campaign Activities
   (c) Scandals and Controversies

Appendix B CLRM Assumption

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Table 10: Checking for CLRM Assumption for Regrsession on Negative Comment

Test	**Statistic**	**Degrees of Freedom**	**p-value**
Jarque Bera Test	14.995	2	<0.001 ***

Table 11: Regression of number of negative comments on video views

Coefficients	Estimate	Standard Error	t-value	p-value
(Intercept)	-2.8215	0.4054	-6.959***	<0.001
Views	0.7056	0.0330	21.369***	<0.001

Residual standard error: 0.6491 on 369 degrees of freedom Multiple R-squared: 0.5531, Adjusted R-squared: 0.5519 F-statistic: 456.6 on 1 and 369 DF, p-value: <0.001

Table 12: Diagnostic tests for regression analysis

Diagnostic Test	df1	df2	Statistic	p-value
Weak instruments	1	367	4507.699	<0.001***
Wu-Hausman	1	366	3.231	0.0731 .

Table 13: RESET test results for first and second stages of regression analysis

Test	df1	df2	Statistic	p-value
RESET (Model 1)	2	365	1.5716	0.2091
RESET (Model 3)	2	365	0.25632	0.774

Table 14: Results of the Studentized Breusch-Pagan Test for Homoscedasticity

Test	BP Statistic	Degrees of Freedom	p-value
Model 1	0.30953	2	0.8566
Model 3	0.31475	2	0.8544

Table 15: Results of the Jarque-Bera Test for Normality of Residuals

Test	X-squared	Degrees of Freedom	p-value
First Stage	128.98***	2	$<$0.001
Second Stage	18.244***	2	$<$0.001

Appendix C Regression of positive and neutral comments against cateogry

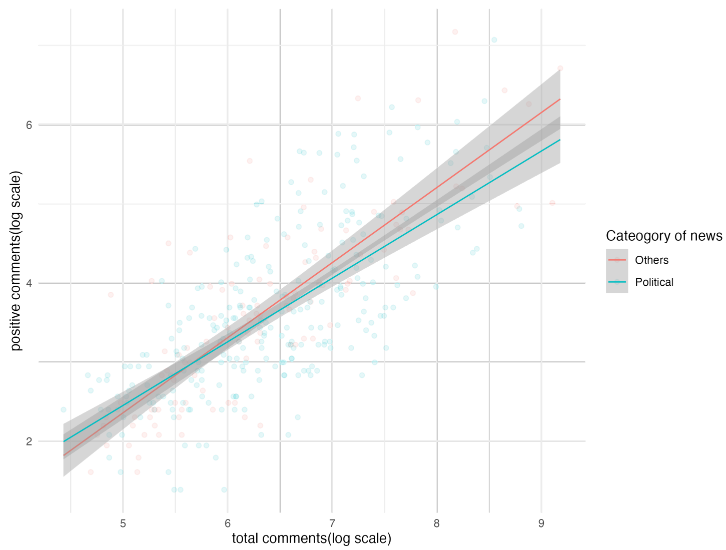
C.1 Coefficient on Positive Comments

Table 16: Multiple regression table for positive comment count

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	-4.49715	0.50180	-8.962	$<$0.001***
$\ln(comment)$	0.49345	0.06966	7.084	$<$0.001***
category	0.03800	0.08257	0.460	0.646
$\ln(views)$	0.40205	0.06444	6.239	$<$0.001***

Note:*,**,*** denote 5%, 1%, and 0.1% significance levels, respectively.

Residual standard error: 0.6969 on 367 degrees of freedom Multiple R-squared: 0.5911, Adjusted R-squared: 0.5878 F-statistic: 176.9 on 3 and 367 DF, p-value: $<$0.001



Note: The shade indicates 95% confidence interval of the model

Figure 5: Multiple regression plot for the effect of news category and total comment count on positive comment count

C.2 Coefficient on Neutral Comments

Table 17: Multiple regression table for the effect of news category and total comment count on neutral comment count

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	-1.96362	0.13379	-14.677	$<$0.001***
$\ln(comment)$	0.84866	0.01857	45.698	$<$0.001***
category	-0.06501	0.02201	-2.953	0.00335**
$\ln(views)$	0.15755	0.01718	9.169	$<$0.001***

Note:*,**,*** denote 5%, 1%, and 0.1% significance levels, respectively.

Residual standard error: 0.1858 on 367 degrees of freedom Multiple R-squared: 0.9623, Adjusted R-squared: 0.962 F-statistic: 3120 on 3 and 367 DF, p-value: <0.001

Appendix D Distributions of variables

D.1 Distributions of comment and views for news

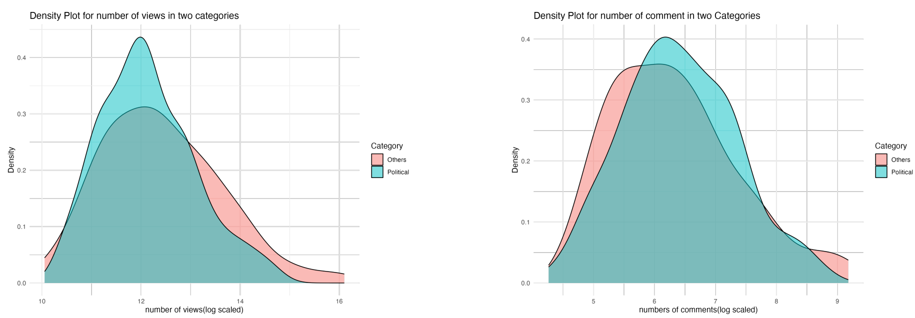


Figure 6: PDF for number of comment and views

Table 18: Two-sample Kolmogorov-Smirnov of the number of comment and views

Variable	D	p-value
comment	0.11254	0.2916
views	0.1688	0.02648*

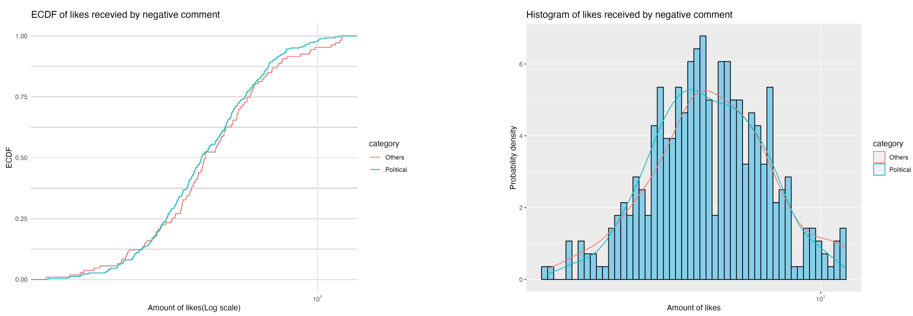
Note:*,**,*** denote 5%, 1%, and 0.1% significant level, subject to a two-sided alternative hypothesis.

Table 19: Two-sample one-sided Kolmogorov-Smirnov of the number of views

Variable	D^+	p-value
views	0.1688*	0.01324

Note:*,**,*** denote 5%, 1%, and 0.1% significant level, respectively. Tested against the alternative hypothesis that the CDF of number of comment for political news lies above non-political

D.2 Distributions of likes received by negative comment



Note: the bar represent the distribution of likes recevied by negative comment in all category.

Figure 7: PDF and ECDF of likes recevied by negative comment by category

Appendix E Regression model for likes received by positive and neutral comments

E.1 Positive comments

Table 20: Multiple regression table on positive comment likes

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	-4.49995	1.64773	-2.731	0.00662 **
$\ln(pos_{c}ount)$	0.43772	0.23972	1.826	0.06866 .
category	-0.02757	0.14285	-0.193	0.84706
$\ln(views)$	0.65272	0.19705	3.312	0.00102 **

Note: *, **, *** denote 5%, 1%, and 0.1% significance levels, respectively.

Residual standard error: 1.183 on 367 degrees of freedom Multiple R-Squared: 0.5263, Adjusted R-squared: 0.5224 Wald test: 91.73 on 3 and 367 DF, p-value: <0.001

Table 21: Multiple regression table on neutral comment likes

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	0.08008	0.46720	0.171	0.864
$\ln(neutral)$	1.13038	0.06477	17.454	<0.001 ***
category	-0.02218	0.06419	-0.346	0.730
$\ln(views)$	0.07225	0.05962	1.212	0.226

Note: *, **, *** denote 5%, 1%, and 0.1% significance levels, respectively.

E.2 Neutral comments

Residual standard error: 0.5499 on 367 degrees of freedom Multiple R-Squared: 0.8125, Adjusted R-squared: 0.811 Wald test: 513.3 on 3 and 367 DF, p-value: <0.001

Appendix F Alternative models

F.1 Coefficient on Negative Comment Interaction Effects

Note:In this model, no observation is classifed as outlier using 1.96 standard deviation as threshold, hence no observation has been removed.

$$\begin{aligned} \text{negative} = \beta_0 &+ \beta_1(\text{comment}) + \beta_2(\text{category}) \\ &+ \beta_3(\text{views}) + \beta_4(\text{comment} \times \text{category}) \\ &+ \beta_5(\text{views} \times \text{category}) + \epsilon \end{aligned} \tag{5}$$

$$\begin{aligned} \text{likes} = \beta_0 &+ \beta_1(\text{negative}) + \beta_2(\text{category}) \\ &+ \beta_3(\text{negative} \times \text{category}) + \beta_4(\text{views}) + \epsilon \end{aligned} \tag{6}$$

Residual standard error: 3028 on 388 degrees of freedom

Multiple R-Squared: 0.779, Adjusted R-squared: 0.7767

Wald test: 349.6 on 4 and 388 DF, p-value: <0.001

Table 22: Multiple regression table for the effect of total comment count and interaction terms on negative comment outcomes

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	-26.180	14.380	-1.820	0.070 .
comment	0.571	0.015	38.573	<0.001 ***
category	22.380	18.190	1.230	0.219
views	-0.00002	0.00002	-1.071	0.285
comment:category	0.145	0.019	7.648	<0.001 ***
views:category	-0.00035	0.00004	-9.348	<0.001 ***

Residual standard error	135.9 on 387 degrees of freedom
Multiple R-squared	0.9666
Adjusted R-squared	0.9662
F-statistic	2241 on 5 and 387 DF, p-value: <0.001

Note:*, **, *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 23: Regression results with coefficients and diagnostic tests.

Coefficients				
Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	-714.70	315.10	-2.268	0.02387 *
negative	10.31	0.505	20.393	<0.001 ***
category	258.30	399.80	0.646	0.5186
views	-0.001081	0.000355	-3.050	0.00245 **
negative:category	-3.33	0.4983	-6.682	<0.001 ***
Diagnostic Tests				
Diagnostic Test	df1	df2	Statistic	p-value
Weak instruments (negative)	4	388	2175.93	<0.001 ***
Weak instruments (negative:category)	4	388	3152.31	<0.001 ***
Wu-Hausman	2	386	18.48	¡0.001 ***

Table 24: Multiple regression table on the impact of negative count and views on the number of likes

Coefficient	Estimate	Standard Error	t-value	p-value
(Intercept)	3.73029	0.40446	9.223	<0.001 ***
$\ln(\widehat{negative})$	0.53973	0.04973	10.854	<0.001 ***
category	-0.16362	0.06867	-2.383	0.01769 *
$\ln(views)$	-0.12233	0.04656	-2.628	0.00896 **

Residual standard error	0.5732 on 366 degrees of freedom
Multiple R-squared	0.3831
Adjusted R-squared	0.378
Wald test	67.67 on 3 and 366 DF, p-value: <0.001

Note: *, **, *** denote 5%, 1%, and 0.1% significance levels, respectively. The standard deviation of $\ln(likes)$ is 0.7268 and the mean is 5.256.

Appendix G Replication package

A replication package of this research is provided at https://github.com/KevincSF/URSS2024