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"Facebook Reactions" as Emotional Indicators: A Multi-Method Approach to Analyzing User Engagement with COVID-19 News on Indian Media Platforms.

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In grateful dedication

To my parents, for their love and sacrifice

To Professor Fabio Giglietto, for his wisdom and guidance

“Facebook Reactions” as Emotional Indicators: A Multi-Method Approach to Analyzing User Engagement with COVID-19 News on Indian Media Platforms.

Abstract

This thesis investigates the role of Facebook reactions as indicators of public sentiment and engagement with COVID-19 pandemic-related news in India during different stages of the pandemic, ranging from March 24, 2020, to March 31, 2022. This work employs a mixed-methods approach combining time-series analysis with embedding-based topic modeling, GPT-4-assisted cluster labeling, and lexicon-based sentiment analysis to examine a dataset of 68,319 Facebook posts and a focused subset of 8,622 Facebook posts analyzed for the early stages of the pandemic (March 24 - April 14, 2020) to capture initial public responses. This data is derived from four major English-language Indian news outlets: The Times of India, The Hindu, Indian Express, and Hindustan Times.

Facebook reactions such as "Love," "Haha," "Wow," "Sad," and "Angry" serve as unique paralinguistic digital affordances that enable users to express their feelings and emotions toward online content and posts. This research explores how these Facebook reactions correlate with news posts and user engagement with news content shared during the COVID-19 pandemic.

By employing time-series analysis, the study identified significant spikes in user engagement, particularly during the early pandemic period, with forty-eight "unusual days" characterized by significant variations in Facebook reactions. Through embedding-based topic modeling, the analysis revealed twenty-five distinct thematic clusters for COVID-19-related news coverage, ranging from technological innovations and lockdown enforcement to global political responses and philanthropic efforts. These distinct clusters demonstrated different patterns of user engagement, with predominantly positive reactions ("Love," "Haha") associated with clusters focusing on community support and celebrity engagement, while negative reactions ("Angry," "Sad") were linked to clusters related to crisis impacts and enforcement actions. Additionally, these patterns revealed systematic variations in reactions across different news outlets.

The analysis revealed that The Times of India achieved the highest engagement overall but showed negative sentiment scores, while The Hindu revealed the most positive sentiment scores despite lower user engagement. This analysis observed a moderate positive correlation (r=0.37) between sentiment and user reactions, indicating that the emotional tone in news posts influenced audience responses. Moreover, the study identified the exploitation of emotional engagement, commonly referred to as "rage-baiting" content, particularly

around communal politics and posts related to China during the COVID-19 pandemic period.

The findings of this study contribute to enhancing understanding of crisis communication in the digital era by illustrating how Facebook reactions can capture nuanced public emotional responses beyond traditional engagement metrics such as likes, comments, and shares. The innovative use of GPT-4 for cluster labeling presents a novel approach for interpreting large-scale social media datasets. The findings offer practical insights and guidance for news media organizations and policymakers to develop strategies for more effective crisis communication during public health emergencies.

Keywords: Facebook reactions, COVID-19 pandemic, sentiment analysis, social media engagement, Indian news media, topic modeling, crisis communication, digital emotional indicators.

Table of Contents

Chapter 1: Introduction 6

1.1 Background and Context 6

1.2 Research Objectives and Questions 11

1.3 Significance and Timeframe of the Study 11

1.4 Methodology Overview 12

Chapter 2: Literature Review 15

2.1 Procedure for Systematic Review 18

2.1.1 The Rise of Facebook Reactions 20

2.2.1 Politics and Far-Right Groups 23

2.2.2 Facebook Reactions in Political Campaigns and Election 24

2.2.3 Facebook Reactions in populist politics 26

2.2.4 Facebook Reactions in Far-Right Politics 27

2.2.5 Facebook Reactions in News and Junk News 29

2.3 Other Social Issues (Sub-topics: Psychological, Sentimental and Emotional, Healthcare, Business and Customer Engagement, Miscellaneous) 31

2.4 Literature Review Conclusion 35

Chapter 3: Theoretical and Conceptual Framework 40

3.1 Facebook and COVID-19 in India 40

3.2 Emotions and Sentiment on Facebook 42

3.3 K-means Clustering for Similar Links and Posts 45

3.4 The Novel Aspects of GPT-4-Assisted Cluster Labeling 47

3.5 Integration of LLM with Academic Research 49

Chapter 4: Data and Methodology 50

4.1 CrowdTangle and Facebook Data 53

4.1.1 Data Collection 53

4.1.2 Data Cleaning and Pre-processing 53

4.2 Time Series Analysis 54

4.2.1 Percentage Change Method 57

4.2.2 Z-score Method with Rolling Statistics 57

4.3 Embedding-based Topic Modeling Using OpenAI APIs 62

4.3.1 Vector Representation 62

4.3.2 Clustering Analysis 63

4.3.3 Dimensionality Reduction and Visualization 63
4.3.4 GPT-4 Assisted Cluster Labelling 64
4.4 Sentiment Analysis 65
4.4.1 Lexicon-based Sentiment Analysis Using the Sentimentr Package 65
4.4.2 User Engagement Matrix and Sentiment Scores 67
Chapter 5: Results and Analysis 69
5.1 Time Series Analysis of Facebook Reactions 71
5.1.1 Overall Trends and Patterns 72
5.1.2 Unusual Days and Sudden Changes in Reactions for Each News Outlet 77
5.2 Topic Modeling and Cluster Analysis 97
5.2.1 Identified COVID-19 News Topics and Clusters 97
5.2.2 Cluster Sizes, Label Coverage, and Cohesiveness 98
5.3 Sentiment Analysis and User Engagement 99
5.3.1 Sentiment Scores and User Reactions across Clusters 101
5.3.2 Relationship between News Sentiment and User Engagement ... 103
5.3.3 Variations in Sentiment and Engagement across News Outlets . 106
Chapter 6: Discussion 108
6.1 Interpretation of Results in the Context of Existing Literature 108
6.2 Potential Reasons for Unusual Patterns and Viral Content 111
6.3 Implications for News Outlets and Social Media Strategists 112
6.4 Limitations and Future Research Directions 114
Chapter 7: Conclusion 116
7.1 Summary of Key Findings 116
7.2 Contributions to the Field 117
7.3 Recommendations and Concluding Remarks 118
References 120
Appendices 153
Appendix A. Supplementary materials for systematic literature review 153
Appendix B. The COVID-19 News Coverage Reaction Analysis for Time series. 170
Appendix C. Text Embedding Generation Using OpenAI API 202
Appendix D. Sentiment analysis for high engagement period 217

Appendix E: Documentation of Viral Facebook Posts During COVID-19 Coverage.....224

Chapter 1: Introduction

1.1 Background and Context

In recent years, we have seen the emergence of social media with the transformation of the landscape of human communication, information dissemination, and sharing of content among users. Among other social media, Facebook stands out as a key player boosting the global reach of 2.9 million monthly active users in 2023 (Newberry, 2023). Recent data shows that Facebook is not only the largest social media platform in India, but also serves as a vital tool for communication, information dissemination, and social engagement across all demographic segments. If we consider Facebook users' demography, approximately 366.9 to 581.6 million users are reported in India, making India the country with the largest number of Facebook users globally (Facebook Users by Country 2024, 2024a; Facebook Users by Country 2024, 2024b; Kemp, 2024b; Kumar, 2024). The percentage of this user base is about 25.6% of India's total population, which reaches approximately 1.4 billion people (Facebook Users by Country 2024, 2024b; Mohammad, 2024). Among users aged 18 years and above, approximately 81.3% are active on Facebook platforms. From January 2023 to January 2024, Facebook's potential ad reach increased by approximately 52 million users, reflecting a growth rate of 16.6% (Kemp, 2024a). This growth shows that users' interest and engagement with

Facebook is still high in India. Facebook is the third-most used social network in India, following WhatsApp and Instagram (Facebook Users by Country (2024), n.d.).

In the context of political discourse, Facebook has become a pivotal platform, and studies have shown that social media significantly impacts voters' decision-making process and political campaigns (Boulianne & Larsson, 2023, 2024; Pecile et al., 2024; Sandoval-Almazan & Valle-Cruz, 2018). A study from Kerala (India) gives insight into how social media usage among voters helped empower younger demographics by reducing reliance on traditional influencers (Balasundaram et al., 2024). The platform has also been used as an instrument to facilitate political movements and discussions around critical topics like gender equality and anti-corruption (Guha, 2022). Even customer behavior is being shaped by social media, particularly Facebook (Manningham et al., 2024; Pagar, 2017; Vaiciukynaite et al., 2023).

Facebook serves as a platform for cultural expression and social movements in India, facilitating discussion around societal issues ranging from gender rights to environmental concerns. The rise of hashtag activism on social media has illustrated and amplified the voices of marginalized groups and mobilized support for various causes (Guha, 2022). Women particularly benefited from this digital media, using it as an awareness tool about the issues affecting them without geographical limitations (Ray, 2013). These dynamics highlight the importance of Facebook's role as a catalyst for understanding contemporary Indian society, making it an essential area of study. Its vast reach and influence across multiple demographics make understanding and researching Facebook critical for insights into the evolving landscape of communication in contemporary India. The cultural shifts viewed through the lens of this social media platform can provide valuable insights into Indian society.

The meteoric rise of this Facebook platform with ongoing evaluation captured the attention of researchers across the discipline, who seek to unveil complex dynamics of social issues, users' behavior, sentiments, and their engagement within this varied virtual ecosystem (Caers et al., 2013; Franz et al., 2019)

The advent moment of Facebook history happened in 2016 when Facebook introduced its “Facebook reaction” as a groundbreaking extension of its iconic “Like” button (Krug, 2016; Turnbull & Jenkins, 2016). It was an innovative feature by which users get empowered to express a wide range spectrum of emotions in response to content or posts, these are “Love”, “Haha”, “Wow”, “Sad”, and “Angry” (Paolillo, 2023; Scott et al., 2020). The integration of "Facebook reactions" made a significant shift in the platform's emotional accuracy by opening a new approach to understanding the nuanced interaction among content, user engagement, and sentiment (Heidenreich et al., 2022; Velazquez-Solis et al., 2023).

This potential transformative approach of “Facebook Reactions” has been noticed by academic and other field of researchers’ communities and recognized this feature as a valuable tool for investigating the complex issues of society, socioeconomic, psychological, and political issues (Anwar & Giglietto, 2024; Godard & Holtzman, 2022; Kosinski et al., 2015). Leveraging the rich data generated through users' interactions with 'Facebook Reactions,' scholars gain unprecedented insights into public opinion, behavior, sentiment, and thinking patterns. This data enables critical analysis of events, political approaches, public debate, political communication, trust, and misinformation in current news events (Kim & Yang, 2017; Tasente & Rus, 2019).

The significance of “Facebook reaction” and its study has been further amplified by the global COVID-19 pandemic. During this period, it profoundly reshaped people’s online engagement with the consumption of news and information. As the whole world grappled with the crisis of the COVID-19 pandemic, online social media became a primary source of updates, news, and information with the discourse of billions of users globally (Ali et al., 2021; Al-Zaman, 2021). In this context, Facebook and its “Facebook Reactions” have played an important role in capturing the emotional pulses of people and served as intermediate indicators for sentiment toward COVID-19-related posts and content (Bagić Babac, 2024; Basile et al., 2018; Larsson, 2024). The interaction through 'Facebook Reactions,' users’ sentiments, and their engagement during the COVID-19 (Coronavirus Disease 2019) pandemic has far-reaching implications

that extend beyond mere curiosity. Understanding how information is received, disseminated, propagated, interpreted, and engaged with on Facebook and other social media platforms is crucial for developing effective communication strategies during crises (Deacon & Stanyer, 2021; Loecherbach et al., 2020).

The COVID-19 pandemic posed challenges not only for health but also gave rise to an unprecedented wave of misinformation and disinformation globally, often referred to as an "infodemic." This term describes the excessive flow of information—including misleading or false content—that circulates rapidly in both physical and digital environments during a public health crisis (Wilhelm et al., 2023). The World Health Organization (WHO) recognized this phenomenon and coined the term to encapsulate the overwhelming amount of information, both accurate and inaccurate, flooding social media platforms during that period (Teodoro et al., 2021; Yesmin & Ahmed, 2022). Understanding the dynamics of this 'infodemic' is crucial for managing effective communication to curb misinformation and disinformation. The "infodemic" remains inherent in our digital communication landscape and needs effective strategies to promote accurate dissemination of information (Evanega et al., 2020).

This "infodemic" has critical implications for public health during the COVID-19 pandemic, especially in South Asian countries like India, where misinformation could exacerbate the health crisis (Gala et al., 2024). Understanding the dynamics of this "infodemic" in India is essential for several reasons. India suffered substantially from the flow of misinformation during the pandemic period. A study revealed that COVID-19-related misinformation tweets were highest for the United States, followed by India. The United States accounted for 58.02% of misinformation tweets, while India followed with 7.33% (Pal et al., 2023). Moreover, the diversity of India's socio-cultural landscape plays an important role in spreading misinformation and its perception. A study conducted in rural areas of South Asia, including India, found that while participants recognized the presence of COVID-19 misinformation in their communities, fewer than 10% found it easy to determine the accuracy of such information (Gala et al., 2024). It indicates that misleading information related to COVID-19 can lead to confusion and mistrust among

people regarding health guidelines and vaccination information. To combat the adverse effects of misinformation, it is imperative to develop public health communication strategies such as accuracy prompts, media literacy education, and clear communication from health authorities (Smith et al., 2023). The COVID-19 pandemic in the Indian context provides the best example for studying health-related misinformation as well.

Moreover, during the COVID-19 pandemic the alarming prevalence on social media platforms like Facebook highlighted the misinformation (Ghasiya & Sasahara, 2022), here the "Facebook Reactions" may contribute to amplifying or suppressing certain narratives. The rapid propagation of misleading information or narratives can put severe consequences for undermining public health, exacerbating social issues and tensions, and eroding the trust in institutions (Tsao et al., 2021; Wang et al., 2024).

Against all these backdrops, this present thesis has aimed to provide an in-depth and comprehensive study and analysis of "Facebook Reactions" in the context of the COVID-19 news coverage in India during the different stages of the pandemic ranging from March 24, 2020 - March 31, 2022. Focusing on this critical timeline, this study seeks to grasp the initial public response to the unfolding crisis, with the role of "Facebook Reactions" shaping public sentiments and engagement patterns. To achieve this objective, we employ a novel and rigorous methodology which is a combination of advanced computational methods and techniques, including embedding-based topic modeling, GPT-4 assisted cluster labeling, and lexicon-based sentiment analysis and time series analysis. Leveraging these cutting-edge techniques, the study uncovers latent themes and topics, sentiment patterns, and engagement dynamics throughout the entire timeline that would not be apparent through traditional methods.

1.2 Research Objectives and Questions

These are the following research questions guiding this thesis-

1. What were the prominent themes or topics of news coverage during the earlier stage of the COVID-19 pandemic for India?
2. Is there any relationship between the sentiments of users across the news outlets?
3. Do the different news outlets show the variation of users' sentiments and engagement for the same COVID-19 topics?
4. How did the users' sentiment and engagement vary across the news outlets?

By addressing these questions this study seeks to contribute to the literature on the "Facebook Reactions" and the role of shaping the public discourse and engagement during the crisis. The findings of this study may contribute valuable information to help evolve communication strategies for combating the spread of misinformation and disinformation. Additionally, this research provides valuable insights into the complex interplay between content, sentiment, and user behavior on social media platforms, particularly on Facebook.

1.3 Significance and Timeframe of the Study

The decision to focus the news coverage on India during the early stages of the COVID-19 pandemic is motivated by several reasons. First, India was one of the most severely affected countries by the COVID-19 pandemic, with millions of cases reported and among the highest mortality rates recorded globally (Gupta et al., 2021); second, the country's highest population has high social media penetration, which gives the advantage to examine the role of social media platforms such as Facebook during the critical period (Measuring Digital Development, 2022). Finally, the earliest stage of the COVID-19 pandemic represents a critical time where information and public responses were crucial to determine the course of the crisis (Kathuria, 2021; Mach et al., 2021).

To ensure nuance and comprehensive analysis, this study relies upon the data driven from four major subscribed and circulated Indian news outlets i.e. The Times of India, The Hindu, Indian Express, and Hindustan Times. Inclusion of multiple news outlets to get a diverse and representative sample of the COVID-19-related topics, contents, and information captures by different editorial perspectives and their targeted audiences, with their reporting styles (Deacon & Stanyer, 2021). This approach not only makes the finding robust but increases the reliability and also enables the identification the variations in sentiment and user engagement patterns all across the different news outlets (Lynch & Peer, 2002).

The study period was chosen from March 24, 2020, to March 31, 2022. On March 24, 2020, Indian Prime Minister Mr. Modi announced a 21-day national lockdown, which was initially set to end on April 14, 2020 (Hebbar, 2020).
This study period concludes on March 31, 2022, when the Ministry of Home Affairs (MHA) of India decided to end all Covid-19 containment measures, except for the use of face masks and social distancing measures ("COVID-19 Curbs End on March 31, Except Masks, Distancing," n.d.; "MHA Ends COVID-19 Containment Measures from March 31; Wearing of Face Mask to Continue," 2022)

1.4 Methodology Overview

The mixed methodology taken into account for this study, represents a significant advantage in the field of social media research, by the combination of embedding-based topic modeling, GPT-4 assisted cluster labeling, and lexicon-based sentiment analysis, this study uncovers the potential of the integration of advanced language processing techniques with social media data analysis gives valuable insight into the public sentiment and their behavior.

Using the embedding-based topic model allows the identification of latent topics and themes with a large corpus of pandemic-related new articles that were shared on Facebook. This approach goes forward to keyword-based analysis which captures semantic relations for words and phrases to find out the

meaningful pattern and its associations (Zhang et al., 2024). Whereas GPT-4 is an innovative language model application used for cluster labeling, this represents a major contribution to the study. Leveraging this model's advanced natural language capabilities, this study demonstrates that GPT-4 can be used to generate descriptive and concise labels for identified clusters, enhancing interpretability and coherence (Colavito et al., 2024; Holmes et al., 2023).

Next, we have used a lexicon-based sentiment analysis which allows for the assessment of the emotion valence that was expressed in the news posts and [in] user reactions. By employing the "sentimentr" package for R (Rinker, 2016, 2015/2024), the analysis accounted for the nuances of language, i.e., mixed sentiments and valence shifters, which provide a more accurate representation of emotional news coverage during the COVID-19 period (Hellín et al., 2023). By providing comprehensive approaches to studying the interplay between news content, user engagement, and their sentiments during the COVID-19 period, this study contributes to crisis management, the role of media in shaping public opinion, and media diversification. The findings of this thesis have both academic and practical applications.

The identification of main topics and variations in sentiment as well as the engagement pattern across the different news outlets could inform the development of a more effective communication strategy for the crisis period. By getting which topics and themes resonate with users and coverage of different news outlets news coverage influences the user reaction.

The methodological part of this study represents and can serve the way of future research as a “blueprint” for the area of social media analysis. Whereas the digital landscape continues to evolve, this pioneer approach in the study would be increasingly valuable to analyze the vast and complex data.

This thesis provides an additional five appendices that contain the supplementary materials supporting the main findings and other additional technical details. Appendix A presents the complete systematic literature review dataset, where 64 analyzed articles are categorized by theme and publication

year. Detailed time series analysis plots and correlation tables for all Facebook reactions across the four news outlets are included in Appendix B. Appendix C provides insight into the technical implementation code for text embedding generation using OpenAI's API. Appendix D pertains to additional sentiment analysis, their visualizations, and outlier cluster analysis. Appendix E is documented with the viral Facebook posts, together with their original URLs, screenshots, and reaction counts, that exemplify the unusual engagement patterns identified in the time series analysis.

In conclusion, this study aims to contribute to understanding Facebook Reactions and their role in shaping audience opinions, public discourse, and engagement. The findings of this research can inform policymaking, guide media outlets, and shape platform development to promote credible information while mitigating the spread of misleading information. The next chapter for the comprehensive literature review for "Facebook Reactions" with their application in various areas and contexts describes data collection, analysis, the method used, key findings, and its implications. We will discuss the limitations and future directions. Through all these efforts, this study aims to contribute to scholarly dialogue, social media analysis, user engagement strategies, and the formation of public opinion in this digital era.

Chapter 2: Literature Review

In February 2016, Facebook expanded the original “Like” button by introducing five additional “Reactions”—Love, Haha, Wow, Sad, and Angry—using modified versions of Unicode emojis. These reactions enable users to express more nuanced emotions towards posts.

Social media platforms provide information and communication among a diverse population in terms of different cultural backgrounds and identities with different opinions (Franz et al., 2019; Park et al., 2021), Facebook has become one of the most dominant and omnipresent social networking sites (SNS), and its rise is an important trend, over the past decade (Caers et al., 2013; Chiou et al., 2014; Lamot et al., 2024). The number of Facebook users is growing by 1.3% year-over-year, which amounts to an increase of 39 million users (Newberry, 2023). In Meta's third quarter 2023 results, Facebook announced that it had 2.09 billion daily active users on average for September 2023, an increase of 5% year-over-year, while Facebook monthly active users were 3.05 billion as of September 30, 2023, an increase of 3% year-over-year (Menlo Park and California, 2023).

Since Facebook’s launch on February 4, 2004 (Onion et al., 2019), its ongoing evolution process has been an interplay between “platformisation” and “infra-

structuralisation"; the Meta (Previously known as Facebook) is subjected to continuous change (Helmond et al., 2019). In 2009, Facebook added the "Like" button, which was, in 2010, added to individual comments to posts (Eranti & Lonkila, 2015). This button and another kind of lightweight affirmation, that is, "Facebook Reactions", served as social cues of acceptance and for interpersonal relationships (Scissors et al., 2016). All linguistic and non-verbal communicative channels are open to interpretation, which can be phatic where the "Like" button facilitates high ambiguity and seems to have a multipurpose reaction for any content worthy of social response.

In 2016, Facebook extended this functionary button to a single positive of "Like" and allowed users to react to SNS content using a limited range of emotional reactions such as "Love," "Haha," "Wow," "Sad," and "Angry"; this function was allowed to expand to comment in 2017 (Jalan, 2023). They represent a light version of Unicode emojis indicated by an icon resembling common graphic substitutions for ASCII emoticons (Paolillo, 2023), which allow users to express how they feel about the contents. The emotion underlying these six reactions is considered to be universal and frequent (Tian et al., 2017) and to convey emotive meaning, including feelings, and moods specific to posts and contents. A Facebook reaction contains less text-based information than comments on a post or writing on the wall, though it is still over-generated content and has valued information at first sight. In particular, as Facebook posts receive more reactions, it becomes more visible and noticeable to other users.

The area of Paralinguistic digital affordance (PDA) is a related light form of non-verbal communication where the response to another person's social media content (Hayes et al., 2016), is used to convey the message and relation-based sentiment where the user clicks a single button and others interpret the meaning (Sumner et al., 2020); thus, "Facebook Reactions" have the nature of PDA. The newly introduced "Facebook Reactions" can better clarify the user's intended meaning, which would not be possible with a single one-click "Like" button; these Reaction buttons are fairly aligned with the desired button where users can focus on the content-based meaning in emotional ways. "Facebook Reactions" can be defined as various non-verbal cues that might save time by

speeding up the rate at which communicators can share information and develop relationships (Sumner & Ramirez, 2017).

If we consider the impact of the Reaction on overall engagement by characterizing different engagement behaviors on two dimensions (i.e., the level of cognitive mode and effort required and the emotional state of expression), reactions—the new feature—inherit the low cognitive effort of “Like” that supports the expressions of major emotional complexity (Al-Rawi, 2019; Sumner et al., 2020); thus, scholars used reactions to investigate user behavior and situation based current topics to measure various aspect of socioeconomic and psychological issues (Kosinski et al., 2015; Godard & Holtzman, 2022), concerning political issues, elections, public debate, health issues, and the trustworthiness of the news about current topics or events. Thus, Facebook provides an environment where researchers can investigate public reactions in a relatively convenient way (Kim & Yang, 2017).

The primary topics related to "Facebook Reactions" were either the introduction of "Reactions and their impact" (Hutchinson, 2016; Turnbull & Jenkins, 2016), "the linguistics approach", or "Emotion detection" (Tian et al., 2017), which seemed to dawn a new era of "Facebook and the user's engagement". However, we have observed that the topics are getting diversified, covering political issues (Tasente and Rus, 2019), human behavior, health, and commerce (Antoniadis et al., 2019). Although there are many articles related to overlapping topics, it is difficult to identify or maintain a particular theme. Nevertheless, the results cover two or more identical results with comparative analysis, and it is possible to put one article into more than one categorized topic.

This literature review investigates scholarly research on user behavior in response to these reactions, with a focus on a broad spectrum of socioeconomic and psychological issues. We conducted a systematic search across databases including Scopus and Google Scholar, using keywords such as “Facebook” and “Reaction,” combined with various key phrases and Boolean operators. Our review synthesizes sixty-four articles published from 2016 to 2023, exploring

diverse topics such as political news, far-right and extremist parties, racism, and hate speech during the COVID-19 pandemic. We organized these articles by theme and publication date. Our meta-analysis reveals that lifestyle and entertainment posts predominantly receive positive reactions, while sociopolitical content tends to elicit a broader spectrum of emotions, including negative sentiments. Furthermore, emotionally charged content consistently attracts higher volumes of reactions, regardless of sentiment.

This review focuses on "Facebook Reactions", examines the literature, and serves as a comprehensive and cumulative approach, summarizing the existing studies and research articles scattered under different subjects and scientific fields. However, it also aims to get comparable results within broader classifications and themes. The main objective of this review is to offer a consolidated and comprehensive perspective to identify the common thread and overarching themes within the literature. By synthesizing all the findings from numerous studies, the review would shed light on the role and impact of "Facebook Reactions". Thus, we seek how "Facebook Reactions" play a role in different or comparable topics and their results. There are other open questions related to "Facebook Reactions", such as the importance of "Facebook Reactions" for the users and correspondence of posts. What aspects of posts or topics are meaningful? Do different topics acquire different reactions and to what extent?

2.1 Procedure for Systematic Review

The focus of the literature review is limited to Facebook. This decision is appropriate because, at present, Facebook is used worldwide and is the most popular SNS (Noyes, 2022; Newberry, 2023). Moreover, the emphasis is based on empirical studies and their findings rather than non-empirical studies. We adhere to the Five step process of systematic review outlined by Briner and Denyer (2012): (1) formulate the research questions, (2) find studies, (3) select and evaluate the studies, (4) analyze the findings, and (5) report the results.

Articles were collected from Scopus, Google Scholar, and other search engines. We used the keywords "Facebook" and "Reaction," with a combination of different key phrases and Boolean operators. In this review, the selected articles are either published in peer-reviewed scientific journals or conferences before proceeding through the same process. The search was performed every month from July to September 2023. It returned a total of 64 articles published between 2016 and 2023 (see Appendix A, Figure 1 for the distribution of articles by year and Supplementary Tables 1-3 for detailed categorization). Matrix and Reference lists were read and scanned with different topics classified across the entire publication time frame (complete article listings provided in Appendix A).

We followed the guidelines marked by Creswell (2009), who states that a review should summarize the cumulative knowledge based on the topic and highlight the issues that research has yet to solve (Table 1).

Topic	Sub-topic
(A) Introduction of Facebook reactions	Introduction to Facebook, language and linguistics.
(B) Politics and far-right groups	(a) Political news, (b) Far-right and extremist parties, racism, hate speech with COVID-19.
(C) Other social issues	Psychological, sentimental, and emotional; health care, business and customer engagement, miscellaneous.

Table 1 - *List of major Facebook research topics.*

The data analysis procedure is as follows. Each empirical article was read and summarized through their research questions including their results and conclusions. Using the comparative naturalistic method (Armstrong, 2010), we read each article and noted the content to examine its tentative research topic. The findings of the article were also noted. The same procedure was repeated with succeeding articles, regardless of whether they were similar to the previous article. If there was any similarity, we placed the article under the first

categorized research topic and then went through another article. We repeated this process for all the articles, although it was possible to categorize one article into more than one research topic.

To provide correspondence between the topic and their content including their result output, we have categorized a wide range of topics/information labeled as (1) The Rise of "Facebook Reactions", (2) Language & Linguistic, (3) Psychological, Sentimental, and Emotional, (4) (a) Political News, (4) (b) Far-right and Extremist Parties, Racism, Hate speech with COVID-19, (5) HealthCare, (6) Business and Customer engagement, and (7) Miscellaneous.
Identified research categorizations appeared to cluster into the major groups – (A) Introduction of "Facebook Reactions", (B) Politics and Far-right groups, and (C) Other social issues. Please find below the table of major groups and topic categorization.

Since Facebook launched its Reaction button, researchers have put their efforts into this new feature. In the beginning, the articles were related to "Facebook Reactions" and their usage, their impact, and their introduction to user engagement. Later, the coverage area of those articles became vast and spread over every field of social issues, ranging from political communication to psychological, sentimental, emotional, health care, business and customer engagement, and so on (Table 1, and Complete article listings and detailed categorizations are provided in Appendix A, Tables 1-3).
The categories are Introduction of "Facebook Reactions" (06 Articles), Politics and Far-right Groups (19 Articles), and Other Social Issues (39 Articles).
Given those categories, in the next section, we describe the type of scientific work, and the main findings identified in each category.

2.1.1 The Rise of Facebook Reactions

Facebook launched "Reaction" buttons globally on February 24, 2016 (Krug, 2016). Facebook named these emojis as love reaction (heart emoji), haha reaction (laughing face), wow reaction (surprised facial expression), sad reaction (sad face), and angry reaction (angry face) (Kluknavská et al., 2023).

Since then, many articles have been published, which have primarily explored the new features and users' engagement with them.

Researchers have been considering and putting their perspectives and opinions on "Facebook Reactions" and "their usage in upcoming days"; for example, Turnbull and Jenkins (2016) examined Facebook's evolution process, and how this new feature provided an opportunity to gain a better understanding of how users engage emotionally. Wisniewski et al. (2020) examined users' feedback about newly introduced features, design implications, and the signification of "Facebook Reactions"; The authors argue that, after the launch, users were more positive about the feature of "Facebook Reactions", and their misconceptions were clarified with actual use. However, there are many constraints including users' inability to express emotions or conflict of emotions.

In the early years, we found articles measuring "Facebook Reactions" from behavioral responses to evaluating emotional responses. Varanasi et al. (2018) argue that "Facebook Reactions" help us to understand relationship maintenance and group cohesion; thus, the new feature has user benefits. Moreover, they found a direct effect of "Facebook Reactions" as "bridging and bonding to social capital" (Coleman, 1988) and a significant relationship between receiving reactions and bridging social capital. This study gives a clear understanding of SNS features, that is, "Facebook Reactions" to the sociopsychological elements of users.

Smoliarova et al. (2018) address the usage of "Facebook Reactions" on social media that correlate with different types of "Facebook Reactions", sharing, and commenting activities. They discussed the possible meaning of the homogeneity of emotions shared on the Facebook community page. Furthermore, the study provides a new pattern and a new insight into user engagement with content on Facebook with its Reaction features. Merrill and Oremus (2021) have found that emojis ("Facebook Reactions") are five times more valuable than "Like," and "reactions" are used as a signal to push more emotionally provocative content. Based on the theory that "Posts that prompted lots of reaction emoji tended to keep users more engaged, and keeping users

engaged was the key to Facebook's businesses," they debated over the "anger" reaction and identified its effect and human judgments that underlie Facebook algorithm.

The concept of Paralinguistic Digital Affordance (PDA) is a light form of non-verbal communication provided in response to another person's social media content (Hayes et al., 2016); it is used to convey the content message and relation-based sentiment where users can click a single button and let others interpret their meaning (Sumner et al., 2020); thus, "Facebook Reactions" allows to explore the nature of PDA.

Sumner et al. (2020) have found that the social media platforms that offer multiple one-click response cues may afford different communicative opportunities than those who have a single PDA response opinion such as "Like" (perceived more faithfully than Reactions); "Like" and "Love" cues were most faithful, whereas other reactions were perceived more deliberate and less automatic communicative behaviors than "Like." Carr et al. (2018) presented explanatory mechanisms behind the use of PDA responses, using the social comparison theory, social penetration theory, and expectancy violations theory for a successful post. They have found that social comparison and communicative reciprocity provide the exploratory power to "Like" and "Reaction" for a successful Post.

On the contrary, Paolillo (2023) found that the reaction distribution across his sample was complex, unstable, and did not reveal a face-work pattern; thus, caution is important for interpreting quantitative analyses for the feature of "Facebook Reactions". Other than English, much research is ongoing to explore the dimensions of "Facebook Reactions" in different languages. Using the Indo-Aryan language Sinhala or Sinhalese used in Sri Lanka (Fernando, 1977), Weeraprameshwara et al. (2022) created a dataset using '"Facebook Reactions" and explored the effectiveness of one-tiered and two-tiered embedding architectures in Sinhala text. In another study for Sinhala Posts, Jayawickrama et al. (2022) considered the Baseline Model to predict "Facebook Reactions" and used the phrase "embedded architecture" as well. Rahman and Seddiqui

(2019) experimented with emotional analysis with the text corpus in the Bangla language consisting of user comments with “Facebook Reactions”.

2.2.1 Politics and Far-Right Groups

Researchers have explored the influence of Facebook and its reaction to political motivation since Facebook launched its Reaction feature globally. In the beginning, Turnbull and Jenkins (2016) predicted that “Facebook Reactions” would be used in different directions or areas as they argued that this feature would be good and useful for evaluating social media campaigns including business purposes, and considered a parameter for emotional objects for communication.

Notably, “Facebook Reactions” is the diversion or expansion of the previous functional approach of the “Like” button (Jalan, 2023). Larsson (2017) presented his analysis of “Facebook Reactions” as the diversification of “Like” for commenting and sharing on the Newspaper Facebook pages. The feature emerged as unpopular compared to the original “Like” functional button, and both negative and positive reactions were used on the newspaper posts. Presumably, users were not too familiar with the usage of “Facebook Reactions”. Bagić Babac (2022) attempted to establish a set of rules by connecting different emotions using “Facebook Reactions” for news posts and comments and measuring positive and negative emotions encoded in the content. She reports that emotion acts as a stimulus to a particular pattern of behavior; positive and negative emotions usually influence positive and negative comments, respectively. Pérez-Seoane et al. (2023) analyzed the publications with the highest volume of interactions and found emotional reactions associated with positive feelings.

2.2.2 Facebook Reactions in Political Campaigns and Election

Subsequently, studies show that politicians are also using social media, especially Facebook to explore its deliberative potential, and their digital followership influences the number of "Facebook Reactions" (Keller & Kleinen-von Königslöw, 2018).

That result was proven in the local election of Mexico where political parties had a large impact with few posts although the candidates had terrible public perception. "Facebook Reactions" opened a path to perceive voters' interest and became a new communication channel, although the election results could not be predicted (Sandoval-Almazan & Valle-Cruz, 2018).

A similar study conducted by Sandoval-Almazan and Valle-Cruz (2020) aims to answer the question of whether the "Facebook Reactions" in Mexico reflect the outcomes of the election in June 2017 and what possible users' emotions are generated with regard to political candidates. That investigation assesses sentiment as an indicator of the mood of public opinion, which could be expressed through "Facebook Reactions" in political campaigns. The finding shows that the winning political party got more negative sentiment, and the parties that got the highest positive sentiment and more reactions over their posts did not win the election. It shows that emotions expressed through reactions are a way of assessing voter behavior that is not easily predicted.

In the Mexican elections, de León and Trilling (2021) conducted a study focusing on positive versus negative political content related to emotional responses, and the degree of influence of the articles that were shared across social media in the context of that election. They found a negative bias in news-sharing behavior and engagement and a great amount of "anger" toward political news. Using a strong dominance of "anger" reaction in that political news during the election, they found that the election was marked with violence and corruption.

Bil-Jaruzelska and Monzer (2022) examined the relationship between emotions and user engagement with political Facebook posts during the Brexit referendum and found that engagement with a post substantially increased when appealing to anger, enthusiasm, and pride. A relationship between appeals to specific emotions (i.e., fear, anger, enthusiasm, and pride) and the engagement of users was observed.

Moreover, with regard to the relationship between topics, emotions, and user engagement, Gerbaudo et al. (2019) analyzed posts and comments through "Facebook Reactions" and found that the positivity of topics was more tended and fairer than negative and controversial issues. They also state that negative campaigning and negative emotions do not always tend to prevail on Facebook, although they found a correlation between positive content and user engagement. Klinger et al. (2023) studied negativity, dramatization, and populist content on Facebook during the election campaigns of the European Parliament election (2014–19) across twelve countries. They found that a higher frequency of likes, shares, and comments had a deeper impact on social media platforms and reached more audiences. Facebook algorithms were changed in 2016 during the election campaigning, and the impact could be observed on user engagement before and after the launching of "reactions." The users had six more responsive options (i.e., like, love, haha, wow, angry, sad), and negative campaigning with posts evoking negative emotions and dramatization yielded more user engagement than other posts. Notably, the populist content also got more user engagement during 2014 before the Reaction button launched.

Furthermore, considering the negative sentiment with user (voter) engagement, Macdonald et al. (2023) have found that negativity is the consistent factor for user (voters) connections on Facebook, where more negative reactions/words generate higher user engagement. According to the authors, candidates strategically employ negativity in their posts to encourage engagement. The increased engagement oftentimes matches the sentiment with the post and negative messages and results in more negative reactions ("Sad" and "anger"). A link exists between a tone set by the candidates who appeal emotionally and

triggers the user who follows the candidate on pages, resulting in increased engagement.

2.2.3 Facebook Reactions in populist politics

In the case of Swiss politicians, a large fellowship and their reactions increase the visibility of political messages or actors and result in more media coverage (Keller and Kleinen-von Königslöw, 2018). Their followership is more prone toward populist parties. A comparison between two populist parties in two countries (Italy and the United Kingdom) shows a measure of emotional response, which is employed as "Facebook Reactions", allowing them to indicate their emotional value over a post that provokes them (Mancosu, 2018).

After "Facebook Reactions" was launched, user engagement saw an unprecedented increase. Klinger et al. (2023) found that negativity, dramatization, including more populist content engaged more in negative campaigning during the European Parliament election in 2019. After examining how populist leaders use Facebook and if they elicit more emotional reactions, Sandberg et al. (2022) have concluded that populist party leaders use Facebook to reach out to their community prolifically. Their posts activate feelings of indignation and trigger responses that are more emotional. The messages posted by populist leaders receive more reactions than only "Like"; in particular, "Haha" and "anger" are prominent. It is interesting that political communication on Facebook triggers emotional reactions and influences the frequency of post-sharing, reflecting sadness with triggered angry reactions (Zerback & Wirz, 2021).

It was unclear whether the popularity of the populist post was driven by the "nature of the message" or "by populist actors" or through both factors' interaction. Blassnig and Wirz (2019) have found that both populist messages and actors influence user perception of the post. Moreover, analyses of populism and user reactions show the effect of populist communication on user reaction. Populist leaders always use populist communication strategies to increase the outreach of their messages and then stimulate the users to interact with the

message, Jost et al. (2020) studied this phenomenon during the German federal election campaign in 2017; they took “anger” and “Love” “Facebook Reactions” into consideration and found exclusive populist message features increase the “anger” reactions, whereas inclusive populism and positive depiction of ordinary citizen lead a high number of “Love” reactions and lesser number of “anger” reactions (Jost et al., 2020). Negative emotions such as anger seem to be reflected when people come across negative information.

Similarly, Kluknavská et al. (2023) have found that leaders mobilize followers through carefully crafted messages that appeal to their emotions. Understandably, political parties use specific messages to trigger negative emotions in their followers to incorporate and mobilize them. Klinger et al. (2023) also showed that political parties across the twelve countries during the 2019 European Parliament elections evoked negative emotions and engaged in more negative campaigning by including populist content in their posts. Donald Trump used messages that frequently got various reactions from, “Love” to “anger,” “Wow” to “Sad,” and “Haha” to “Like”; however, the posts that generated “Love” and “Sad” reactions received the highest user engagement compared to others (Tasente & Rus, 2019).

2.2.4 Facebook Reactions in Far-Right Politics

The “Facebook Reactions” feature provides opportunities to investigate global emotional responses to political messages on Facebook, which is a common platform. Muraoka et al. (2021) described a new measure and presented a dataset of 690 political parties in 79 democracies. They studied “Love” and “anger” reactions to the posts and measured the potential usage of emotional responses, with party-wise variation in the frequency of such reactions. Their results for parties received systematically different proportions of the popular reactions “Love” and “anger,” which depended upon the ideology, party line, and populist orientation. The greater emotional responses came from more extremist parties; other nationalist, populist, and right-leaning parties received a relatively higher proportion of “anger” reaction as well as emotional polarization. Negative and volatile categorical reactions such as “anger,”

“haha,” and “Wow” primarily drive controversy, with a high sharing ratio of controversial news. Oliveira and Azevedo (2023) reveal that negative emotions do not always indicate the presence of hate speech and negativity. These are implications for detecting hate speech.

Considering the example of the Belgian far-right political party, Vlaams Belang, Matamoros Fernandez (2018) noticed that the party used Facebook reaction to spread anger and the audience responded to their call by posting more emojis to express their rage and racist tropes. She explored everyday racism manifested on Facebook as a combination of platform affordances with emojis. Thus, the study of emoji is also related to visual content, hate speech, and content moderation.

It was unclear which features of Facebook appealed to far-right groups and how these features influenced users who incorporated far-right themes and narratives, Hutchinson and Droogan (2022) attempted to find these answers by conducting a cross-national comparative analysis over three years (2016–2019) using data from 59 Australian and Canadian far-right extremist groups on Facebook. Here, the level of user engagement with the posts was assessed using “Facebook Reactions” and identified the themes and narrative and generated user engagements, which mostly comprised six “Facebook Reactions”. In-depth, the qualitative analysis of the narrative and themes show that the highest user engagement is found with “anger” and “Love” reactions paired together. These two reactions were the most frequently used, particularly in narratives and themes relating to in-group and out-group dynamics. Additionally, algorithms further amplified the visibility and impact of these reactions within these groups (Hutchinson & Droogan, 2023).

Inciting public anger, especially raising controversial issues, is a rewarding tactic to increase motivation and contribute to high threshold interaction. Gerbaudo et al. (2023) called it “anger-triggering communication.” They state, “[t]he right-wing populists have a significantly higher number of ‘Angry’ “Facebook Reactions” per post compared to their political adversaries; there is a positive and significant effect of the number of Angry reactions on the number

of times a post is shared; Angry reactions and Shares are overrepresented in posts on immigration and security, but anger-fueled mobilization is not limited to these topics" (Gerbaudo et al., 2023). Their findings contribute to the understanding of emotional communication, populism, the effectiveness of negative campaigning, and its mobilization.

2.2.5 Facebook Reactions in News and Junk News

In a particular topic such as mis/disinformation, how do users make sense to interact with political junk news on Facebook, how is the "emotional architecture" constructed to intervene in this sense-building or interactive process? These questions were addressed through topic modeling of 40,500 junk news articles. Savolainen et al. (2020) explore the interplay between junk news, the audience, and Facebook's emotional architecture, generating bivalent emotional logic. "Love" and "Angry" rarely co-occurred and strongly correlated with other reactions. Savolainen et al. (2020) contend that the "anger" reaction seems to co-occur predominantly with the "Sad" and "Wow" reactions, whereas the relation between "like" and "Love" reactions contains high positivity. This division of Facebook posts between positive and negative carried out further arguments for the characteristics of junk news engagement.

Another research was carried out by Sturm Wilkerson et al. (2021) about the interaction between the "hyperpartisan" news content on Facebook and audience reactions in the US in 2016. The study combined political communication, social media, affective intelligence, and emotional symbolism. It then examined both the messages on political-leaning Facebook pages and the audience responses to hyperpartisan content. The research question addressed the content of hyperpartisan posts on Facebook, with the relationships between content and users' engagement. The authors found that social media messages contained more "anger" reactions for audiences of both right- and left-leaning pages (Sturm Wilkerson et al., 2021), and news generating negative reactions were circulated and shared more than those generating positive reactions. The study found the emotional appeals for the prediction of "Facebook Reactions". Basile et al. (2018b) presented a study based on the "Facebook Reactions"

feature to predict the entropy of a post's reactions; the reactions were further measured as a proxy to predict the controversy of news, resulting in high entropy (high reactions) with bigger controversy.

During the Mexican elections in 2018, de León & Trilling (2021) conducted a study focusing on positive versus negative political content related to emotional responses, and the degree of influence of the articles that were shared across social media in the context of that election. They found a strong relationship between the "Sad" reaction and negative news and between the "Wow" reaction and negative news. The last finding shows that the "Wow" reaction is used as a negative expression (i.e., disbelief rather than amazement) when it comes to political news. They also found a bias in news-sharing behavior and engagement with a great amount of "anger" reaction to political news marked with violence and corruption.

In a significant case of the former British colony Hong Kong, where a political movement was ongoing after the National Security Law was passed, Nip and Berthelier (2023) conducted a study to understand the impact of cultural disparities on emotional responses to political news. They found that China-critical news pages expressed the highest emotional intensity (expressed the most anger); however, their news-sharing correlates with "Wow" and "Sad" reactions. While readers of China's media in Hong Kong had expressed the lowest emotional intensity ("Love"), China-supporting media readers fell in between them. Savolainen et al. (2020) argued and discovered that the interplay between junk news (producers), the audience, and Facebook's emotional architecture generates a bivalent emotional logic: "Love" and "anger" reactions rarely co-occurred and correlated most strongly with other reactions.

2.3 Other Social Issues (Sub-topics: Psychological, Sentimental and Emotional, Healthcare, Business and Customer Engagement, Miscellaneous)

In social media, emojis are used widely and are commonly assumed to express the emotional state of the user (Tian et al., 2017). Since February 2016, Facebook users have been able to express their emotions in response to the newly introduced "Facebook Reactions" feature (Pool & Nissim, 2016), which allows users to express their psychological emotions and feelings regarding published content (Raad et al., 2018). This feature of Facebook helps to better understand the users and collect information on their preferences and likeness to be used in different areas such as business and advertisements (Hutchinson, 2016; Baldwin, 2021) or healthcare (Rovetta, 2022).

Tian et al. (2017) consider that social media is not only for sharing information but for the expression of emotion. Consequently, they argued over the upscaled size, genres, and languages or cultures dataset for investigating the types of emojis used in different emotional contexts. They found that "Facebook Reactions" is a good data source for investigating the indicators of users' emotional attitudes. Reliable "Facebook Reactions" such as "anger" and "Love" indicate overall sentiment. Moreover, there is a correlation between Facebook's reactions and emoji usage. Thus, emojis can be used to detect users' sentiments too. Giuntini et al. (2019) made it possible to determine the polarity (positive, negative, and neutral) of "Facebook Reactions" and their correlation with emotional expressions; they suggested that the use of reactions could increase confidence in determining the emotions for the contents and emotional reflection of users.

If we consider the collective attitude and performance through image circulation on Facebook, the reaction button makes it possible to study them. Geboers et al. (2020) used a relational approach to determine photos that have had audiences and been contextualized with mixed reactions, often showing a correlation between "Sad" and "anger" as well as "Love" and "sad." Pool and Nissim (2016) conducted a study before to explore the potential of using "Facebook

Reactions” to perform emotion classification. They were finally able to develop a single model for each emotion classification. A similar approach was made by Raad et al. (2018) to create a framework for predicting the reaction distribution on Facebook posts. They examined the potential Facebook reaction usage, recognized classified emotions, and found the result through their dataset, which revealed that “Like,” “haha,” and “love,” were the most frequently used “Facebook Reactions”. Graziani et al. (2019) proposed the task of emotion classification and prediction of “Facebook Reactions” and warned that “Facebook Reactions” could easily become ambiguous in mapping emotion classes. Later, Wisniewski et al. (2020) identified many design constraints of the “Facebook reaction” feature and users’ inability to express conflicting emotions.

Studies analyzing the news stories circulated on Facebook platform with relation to "Facebook reactions" reveal nuanced patterns of user engagement shaped through the nature of news events and the emotional responses they evoke. Research across different topics and news events has also found that users' decisions to Like, Share, or comment on news posts are influenced by many factors, and unexpected events tend to generate more reactions than others (Salgado & Bobba, 2019). Comments are more likely on news events that align with traditional values such as personal choice or negativity, suggesting users engage more in-depth with stories that provoke strong emotional or personal relevance (Salgado & Bobba, 2019).

Additionally, the "emotional" reactions on Facebook tend to reflect the valence of news stories or particular events, such as positive emotions like "Love" being associated with entertainment and lifestyle content, with sadness and anger reactions being prevalent in sociopolitical or crisis-related news stories (de León & Trilling, 2021; Pratama & Firmansyah, 2022). In the digital environment, the importance of visual cues is established; i.e., emotional reaction icons have a strong influence on vaccination drive communication beyond textual messages (Lee et al., 2024).

Furthermore, a study focused on the COVID-19 pandemic highlights how 'Facebook reactions' serve as heuristic cues guiding users' attention and interaction levels (Masullo, 2022). According to Masullo (2022), 'Like' and 'angry' reactions for COVID-19 news posts were strong predictors of high commenting frequency, suggesting that indicators of emotional engagement through reactions could stimulate further discussion. Thus, pandemic-related content in the Army's posts showed a significant correlation with increased total user engagement through shares and reactions (Kleiner, 2024).

For instance, the analysis of user engagement on WHO's official Facebook page during the COVID-19 pandemic reveals distinct patterns of Facebook reactions across different topics and categories. Posts related to vaccination attracted a higher percentage of 'Like' reactions than other COVID-19 related topics, while showing substantially lower percentages of 'Angry' reactions on the same vaccination topics (Erinç et al., 2024). These findings emphasize how Facebook reactions not only reflect users' emotional responses to news but also influence the visibility and circulation of news stories, shaping public discourse on the Facebook platform (Masullo, 2022; Salgado & Bobba, 2019).

Using Big Five personality and narcissism theories, aimed to investigate how users used “Facebook Reactions”, over which content, and what personality factors motivated them to use. They found that the audience used more positive than negative reactions, concerning the established online norms and with positive self-presentation. They put reactions on status and updates, images, and at least for events. Furthermore, “Reaction use is predicted by high neuroticism, extraversion, and openness, and low narcissism, with these factors driving the use of the strong love reaction, the negative sad and angry reactions, and on the specifically personal time-hop content, possibly motivated by a desire for complex social interaction and to positively manage online interactions, and on the and pictorially salient picture and link content types”. If we consider emotional content, according to Paletz et al. (2023), emotions are associated with posts either positive or negative or both, and relatively lower and higher degrees of activation/ arousal emotions, even if they control the number of followers and “Facebook Reactions”.

In recent years, a phenomenon has emerged on social media platforms as a driving tool for online engagement. This practice involves creating content designed to provoke and incite visceral anger and outrage, leveraging the emotional responses of users to amplify visibility and interaction (Gruet & Lawton, 2024). As we know, the introduction of 'Facebook Reactions' in 2016, an expansion of user expression beyond the 'Like' button, provides opportunities for manipulative content strategies (E. M. Sumner et al., 2018; S. A. Sumner et al., 2020). It also enables nuanced emotional responses to posts and content, but their algorithmic weighting inadvertently prioritized negative emotions. Related research indicates that posts eliciting 'Anger' or 'Sad' reactions received more than double the shares compared to posts with positive reactions (Basile et al., 2018; Sturm Wilkerson et al., 2021).

The 'Facebook Reactions,' especially 'Angry,' has been weaponized by political actors and influencers for diversifying content. For example, Vlaams Belang, a Belgium's far-right party, systematically used provocative posts about immigration to trigger 'Angry' reactions, which Facebook's algorithm interpreted as high engagement, thus increasing the content's reach (Matamoros Fernandez, 2018). Studies show the platform rewards 'rage-baiting' through monetization programs such as Meta's performance bonuses, tied with engagement metrics and creators' payouts. In 2024, a study revealed that creators who used rage-baiting as a strategy earned 37% more revenue than others focusing on positive content (Gruet & Lawton, 2024). It has become an economic model that reinforces the production of polarizing materials and content, as evidenced by a 214% increase in 'Angry' reactions during the 2020 election period on US political pages (Larsson, 2024).

If we consider the psychological and societal impacts of rage farming, it capitalizes on cognitive biases which are rooted in the detection of threats. Studies related to neuroimaging show that anger-inducing content activates the amygdala 68% more than natural or neutral stimuli, resulting in addictive engagement patterns on social media (Mane et al., 2024). This neural response is exploited by influencers whose content generates high revenue primarily

through hate-based and hate-driven comments or shares (Gruet & Lawton, 2024). Here the societal consequences are profound. Through the analysis of Hong Kong's COVID-19 related posts, it shows 'Anger' reactions correlated with a 19% increase in protest participation offline (Wang et al., 2024). Similarly, the murder of George Floyd's video spread virally - facilitated by 'Angry' reactions - demonstrated how platformed outrage can scale movements globally (Patel, 2023).

Notably, Meta's efforts for mitigation of rage-baiting remain hindered by other conflicting priorities. The company introduced fact-checking resulting in the reduction of misinformation across the platform. In 2024, their audit revealed that about 42% of posts flagged for hate-speech had accrued "Angry" reactions prior to being removed (Graziani et al., 2019). This latency allowed the harmful posts to achieve virality before the intervention of moderation.

2.4 Literature Review Conclusion

This study suggests that “Facebook Reactions” have been extensively studied as specific indicators of engagement across various broad topics. We found the basic five “Facebook Reactions” with their nuanced patterns of reaction distribution based on specific research areas and topics. Our analysis suggests that “Love” and “Haha” “Facebook Reactions” are always considered positive responses; however, in certain cases, the “Haha” and “Wow” reactions can be negative engagement indicators with ambiguous meanings. “Sad” and “anger” are always negative indicators of interactions.

Individual articles can draw different conclusions; although in the major combined topics, we have found a unique similarity, especially for Politics and Far-right groups, where emotion plays an important role in user engagement with “Facebook Reactions” and content. A particular pattern of behavior observed in the studies under analysis is that positive emotions usually influence positive comments with positive reactions, while negative emotions influence negative comments with negative reactions on Facebook. The negative sentiment with user engagement demonstrates that negativity is the consistent

factor for user connections on Facebook, and more negative reactions generate higher user engagement. It is interesting that political communication triggers emotional reactions and influences the frequency of post-sharing with sadness and angry reactions. Thus, these populist communication strategies increase the outreach of their messages and stimulate users' interactions with "Facebook Reactions". In addition, a relationship exists between specific emotions such as fear, anger, enthusiasm, and pride with the engagement of users.

As social media expands, users increasingly interact with different topics and their areas of interest with different current challenges. The researchers frequently used different data sources and collection methods. Combined with the complexities of the subject, the absence of a unified source of Facebook data may have contributed to some conflicting results. The matter of concern was not only a unified data source but also the overlapping of research topics, whereas "Facebook Reactions" played an intermediary role in determining various degrees and intensity of the user's psychological and emotional levels with many contrasts and other factors of sociocultural norms, which always differed into certain geographical areas and their cultures. Thus, the outcome of those studies always seemed to differ.

An increasing number of studies were found with quantitative data, which were obtained by Facebook, although they were neither up to date nor relevant but for a specific time duration. Those studies have provided insights into users' behavior and "Facebook Reactions" dealing with wide areas and different topics. However, event-based tabloid topics, including those concerning sensational or scandalous subjects, were always ignored.

We were expecting Cultural Studies and Cross-Cultural Analysis of "Facebook Reactions", either as a comparative or interpretative study across the different cultural contexts. The versatility of "Facebook Reactions" could be used for studying a wide range of fields with the integration of interdisciplinary collaboration and other studies. Researchers could examine the patterns of "Facebook Reactions" within online communities and subcultures, such as niche interest groups, hobbyist communities, or fan groups. From this

perspective, the availability of advanced large language models that can categorize large volumes of social media content more effectively and with less resource expenditure opens intriguing possibilities for analyzing how reactions to posts vary across different topics.

The future of Facebook's reaction is likely to be multifaceted, overlapping a wide range of disciplines, and integrating with other data sources and research methodologies. We hope upcoming research will continue to refine the approaches in the exciting area of "Facebook Reactions" and user engagement with Misinformation and Fact-Checking, Digital-Activism and Social Movements, and so on.

This comprehensive literature review gives the overview of different highlighted key themes and the gaps that still exist in current literature for Facebook and "reactions", particularly in the context of very important issues like COVID-19 and its news coverage. These insights are directly attached to our research questions and methodological approaches.
The diverse applications of "Facebook Reactions" have been studied within different domains such as politics to business and health communication, this diversity underscores the potential usage of "Facebook Reactions" as the indicator of public sentiment for our study about the COVID-19 news coverage in India.

Many studies have demonstrated that different news or events' content got emotional responses from audiences, which are reflected through "Facebook Reactions". Thus, this finding supports our study to analyze "Facebook Reactions" across news outlets and topics related to the pandemic.
Therefore, the connection justified the combination of sentiment analysis and user reaction to get a comprehensive understanding of the public response to the COVID-19 news.

The literature suggests that user engagement tends to change over some time particularly for the news topic or during the crisis events. This observation is fit for our study to decide to employ time series analysis for identifying the unusual pattern of User engagement through the “Facebook Reactions” throughout the pandemic period. The topic modeling has not been extensively covered and practiced with “Facebook reaction” so far, thus, it has proven valuable in the area of social media research. Our approaches such as the use of embedding-based topic modeling with GPT-4 assisted labeling aim to address this gap.
Our research focuses on different media news outlets to address how cultural contexts influence audiences to use “Facebook reaction”, it can be considered cross-cultural social media research.

These connections between the existing literature and our approaches for research validate the methodology while highlighting the potential of our study to contribute new insights. With the combination of those metrics, we aim to prove the comprehensive understanding of Indian audiences on Facebook and their engagement with COVID-19 news on Facebook throughout the pandemic. The research questions which are outlined in Chapter 1 are directly informed by this literature's findings, seeking the established patterns and the gaps in existing studies. The methodological part is detailed in the following chapter, which is designed to answer those questions with the contributions of meaningfulness to the research on social media engagement during the global crisis.

In Chapter 2, we establish the theoretical foundation for understanding "Facebook reactions" as an indicator of public sentiment and engagement, particularly highlighting their role in news dissemination and crisis communication. Chapter 2 demonstrates how "Facebook reactions" have been studied across various domains including politics, health communication, and social movements. This groundwork leads us to Chapter 3's conceptual framework, which examines the role of Facebook during the period of COVID-19 in India. Chapter 3 builds upon that previous knowledge to focus on that application in understanding public response to pandemic-related news. Furthermore, Chapter 3 extends the methodological insight gained from the previous studies by including other approaches to addressing the gaps identified

in the literature review. This integration of the established theoretical frameworks and methodological approaches provides the foundation for analyzing how "Facebook Reactions" reflected and shaped public discourse during the COVID-19 pandemic period in India.

Chapter 3: Theoretical and Conceptual Framework

3.1 Facebook and COVID-19 in India

The COVID-19 pandemic had a profound negative impact on the world, impacting the global communication landscape. India was one of the most affected countries, suffering from millions of infection cases and a high mortality rate. The COVID-19 pandemic profoundly reshaped the digital communication landscape in India, with Facebook emerging as the main digital platform where information was disseminated in public discourse.

As one of the countries most affected by the COVID-19 pandemic and having the largest number of Facebook users, India presents an ideal case study for examining how social media shaped public understanding and responses to information during the period of crisis. Social media played an important role during this era in disseminating information, raising awareness, and shaping public opinion in India.

At the beginning of COVID-19, the rapid spread of the virus was observed, followed by the period of lockdown. It became the main topic that surged in news coverage. The information presented and received by the public was crucial during the COVID-19 crisis.

Studying COVID-19 through the lens of social media is crucial for many reasons, especially in the context of India. This pandemic significantly affected different sectors of life, including economics, public health, social behaviors, and information dissemination, making it an important area of research. Understanding public health, decision-making, and perception of the pandemic is vital for policymaking and communication. Analyzing news coverage that influences public opinion, and perception can help mitigate mis/disinformation and improve health outcomes. The media plays an important role in shaping public opinion and perception during health crises. Accurate and timely media representation of COVID-19 news could influence individual behavior, such as adherence to hygiene and health guidelines. Previous studies indicate that media coverage must be timely and actionable to encourage compliance with preventive measures (M. Gupta et al., 2021; Mach et al., 2021).

Facebook and Facebook reactions played a significant role in influencing public perception of COVID-19 news, shaping how information was received and interpreted. These influences can be understood through different dimensions (Yavetz & Aharony, 2023). Facebook reactions (such as "like," "love," "haha," "angry," "wow," and “Sad”) serve as intermediate indicators for public sentiment toward news articles or Facebook posts (Bagić Babac, 2024; Basile et al., 2018; Larsson, 2024). Positive reactions can enhance the credibility of information, leading users to perceive the content as more trustworthy. On the other hand, negative reactions can trigger skepticism and distrust, potentially leading to the spread of misinformation.

Researchers indicate that emotional responses on social media can significantly affect the information shared among users, potentially amplifying some narratives while suppressing others (Ali et al., 2021; Jones et al., 2021). In India, where social media has become the primary source of information for the public, people may accept or reject health-related information, guidelines, or news based on the prevailing sentiment reflected in reactions (P. Gupta et al., 2020; Tsao et al., 2021).

During the COVID-19 pandemic, the rapid spread of fake news was exacerbated through social media platforms, including Facebook (Ghasiya & Sasahara, 2022; Giglietto et al., 2022). The interplay between "Facebook reactions" and dis/misinformation is a main concern. Researchers inadvertently confirmed that misleading information engaged many users with sensational content, eliciting emotional responses. A portion of the population relies on social media for COVID-19-related information, and their heavy engagement with content shared on these platforms is well-documented (Ali et al., 2021; Al-Zaman, 2021).

3.2 Emotions and Sentiment on Facebook

Emotion is a complex concept with multidimensional characteristics reflecting human personality and behavior. The American Psychological Association describes emotion as "a complex reaction pattern, involving experiential, behavioral, and physiological elements, by which an individual attempts to deal with a personally significant matter or event." Izard (2009) described emotion feeling as a phase of neurobiological activity, a key component of emotion and emotion-cognition interaction.

If we consider about sentiment and emotion, they have always seemed to be an integral part of human experience, influencing behavior, decision-making, and interpersonal communication. Where Emotion refers to a complex psychological state where three distinct components are always involved, these are subjective experience, a physiological response, and a behavioral or expressive response. For example, emotions such as fear, anger, happiness and sadness would significantly affect the situation of individual perceptions with inactions to others (Keltner & Lerner, 2010).

Sentiment, on the other hand, is defined by Merriam-Webster as "an attitude, thought, or judgment prompted by feeling" or "a specific view or notion: opinion." Munezero et al. (2014) noted that "Sentiments are enduring emotional dispositions that have developed over time about particular objects. Conclusions about sentiments in the text have to be performed for a period." In contrast, the evaluative aspect of emotions expressed in language - typically it is described and categorized as positive, negative, or neutral - is considered as sentiment (Pang & Lee, 2008).

While emotion and sentiment are distinct entities, they are often used interchangeably due to the lack of agreed-upon definitions. Sentiments generally represent the polarity of emotion (i.e., positive, negative, or neutral) (Gross, 2020; Munezero et al., 2014). For example, if someone expresses happiness, their emotion is "happy," while their sentiment is "positive" (Sailunaz & Alhajj, 2019).

In the context of social media, distinguishing between emotion and sentiment is crucial. Emotion refers to a person's immediate, subjective feelings, such as happiness, anger, fear, or sadness. Sentiment, however, represents a person's overall attitude or opinion about a particular event, topic, or entity (Gross, 2020; Khan, 2022). Sentiment analysis, widely used in media analysis and marketing, helps understand public opinion and emotional responses to particular events or products (Liu, 2012). The interplay between sentiment and emotion is important for understanding human behavior in both personal and social contexts, as highlighted by the role of emotions in shaping public discourse and media narratives during crises such as the COVID-19 pandemic (González et al., 2008).

The introduction of "Facebook Reactions" was basically an extension of the "Like" button with five additional options: "Love", "Haha", "Wow", "Sad", and "Angry" (Paolillo, 2023; Turnbull & Jenkins, 2016). These reactions provide unique opportunities for researchers to study how people feel about Facebook-shared content, enriching user interactions and engagements (Heidenreich et al., 2022; Velazquez-Solis et al., 2023). Moreover, these emotional indicators, i.e.

'Facebook reactions,' can be measured to analyze public sentiment regarding specific events or topics (Pratama & Firmansyah, 2022; Tula et al., 2022). In 2020, "care" was added to this set.

During the COVID-19 pandemic, Facebook reactions became particularly relevant. Users could articulate their feelings and emotions about pandemic related posts, including health updates, personal experiences, community support, and news. Zhang et al. (2022) studied over 200,000 posts related to COVID-19 vaccination and found that while the overall sentiment was positive, fear and sadness were also present after the approval and trial results of vaccines.

The pandemic highlighted generational differences in using Facebook reactions. Tula et al. (2022) investigated four generations (Baby Boomers, Generation X, Millennials, and Post-millennials) and found that Baby Boomers were the most active users of emojis and Facebook reactions during the initial period of the COVID-19 pandemic.

The surge of misinformation and disinformation during the pandemic significantly influenced user engagement on Facebook (Giglietto et al., 2022). Wahab et al. (2021) revealed that misinformation about COVID-19 was widely spread, leading to confusion and fear among users. Wang et al. (2024) examined emotional responses to news on Facebook and found them to be predominantly negative, associated with public distress and anxiety.

Despite the advantages of Facebook reactions in expressing user emotions, analyzing sentiment on social media presents challenges. These include the ambiguity and fluidity of language, diverse communication methods, and the huge volume of data (Anwar & Giglietto, 2024). To address these challenges, researchers are developing more sophisticated techniques, such as machine learning algorithms for detecting hate speech by analyzing emotional content in social media posts (Rodriguez et al., 2022).

Understanding the interplay of emotions, Facebook reactions, and user engagement during the COVID-19 pandemic requires special attention from researchers. This insight into unprecedented times enhances our understanding of digital behavior patterns and user behavior during crises, potentially informing effective communication strategies for social media platforms.

3.3 K-means Clustering for Similar Links and Posts

Topic modeling, described by Puschmann and Scheffler (2016) as a set of computational methods for analyzing text by identifying patterns in word distributions, treats texts as "bags of words" where each word is a distinct feature. This technique originates from computational linguistics and matrix processing mathematics.

Clustering, a technique for partitioning elements in a dataset based on similarities, assigns similar elements to the same cluster and different elements to separate clusters (Bhatia, 2004). The K-means algorithm, a popular machine learning method, aims to divide M points in N dimensions into K clusters while minimizing the within-cluster sum of squares (Hartigan & Wong, 1979). Steinley (2006, p. 02) described K-means as "designed to partition two-way, two-mode data (that is, N objects each having measurements on P variables) into K classes (C1, C2….CK), where Ck is the set of nk objects in cluster k, and K is given."

The goal is to minimize variance within clusters and maximize variance between clusters. K-means is favored for its simplicity and effectiveness with large datasets. The optimal number of clusters can be determined using the elbow method or silhouette analysis, which measures how similar an object is to its own 'cohesive cluster' compared to other 'separated clusters' (Sinaga & Yang, 2020; Siriya Phoonokniam et al., 2022; Syakur et al., 2018). Many variants of K-means algorithms have been proposed to overcome various impediments (Ahmed et al., 2020).

Identifying clusters and visualizing them in 2-D plots is crucial for understanding any dataset (Rakhlin & Caponnetto, 2006). K-means clustering has diverse applications across various fields. Siriya Phoonokniam et al. (2022) studied its use in analyzing the feasibility of implementing electronic voting systems in Thailand, particularly in Bangkok. Jumb et al. (2014) presented an approach for color image segmentation using K-means clustering by converting images to the HSV (Hue, Saturation, Value) color space. In education, K-means clustering has been implemented in a hierarchical teaching model based on an improved Particle Swarm Optimization (i-PSO) algorithm to enhance personalized educational experiences (Y. Zhang et al., 2016). Su and Chou (2001) applied a novel nonmetric distance measure for clustering, the Symmetry-based version of k-means (SBKM), for face detection. Xu et al. (2017) applied Load pattern Hierarchical k-means (H-Kmeans) to a large-scale Advanced Metering Infrastructure (AMI) dataset for better clustering performance in big data problems.

Other variants of K-means algorithms have been developed for specific applications. Wu and Peng (2017) proposed a wind power forecasting model combining K-means and BPNN (Bagging Neural Network). Yang and Wang (2017) established a traditional K-means clustering algorithm with min-max similarity (MMS) for latent semantic analysis (LSA) of social tags. Manju and Lenin Fred (2018) proposed a unique optimization algorithm for the segmentation and compression of compound images, using an AC coefficient-based segmentation method with the K-means cuckoo optimization algorithm (K-COA), inspired by the brood parasitism of cuckoo birds.

3.4 The Novel Aspects of GPT-4-Assisted Cluster Labeling

Large Language Models (LLMs) have extraordinary capabilities to demonstrate various tasks of Natural Language Processing (NLP), they offer translation of texts, text generation, formulation of questions and answers, text summarization, sentiment analysis, and numerous other services following their training phase (Raiaan et al., 2024). It became an important part of computing the language processing models to understand the verbal pattern and to generate coherent or appropriative replies in certain contexts as well.

OpenAI introduced GPT-4 on March 14, 2023, after the subsequent version of its language model GPT-3, it is a transfer-based model, that can analyze textual and visual data and produce the output (Fan et al., 2023; OpenAI et al., 2024). The GPT-4 has greater efficiency and more dimensions than its predecessor GPT-3, to generate more comprehensive extraordinary capacity and exhibit a higher level of human-like text (Hadi et al., 2023). The recent development of LMMs, especially GPT-4 and later Gemini, expanded the boundaries beyond their traditional tasks with integrated visual understanding and acting on the web agent (Zheng et al., 2024).

These models also have multilingual variants and are trained with multilingual data, these multilingual models across the language is an active area of research as well (Bender et al., 2021). Many Organizations such as Google, Mistral AI, OpenAI, Meta, and Anthropic; developed LLMs that offer versatile natural language processing (NLP) workflows. They are pre-trained language models that are designed for general purposes, their prompt inferences are used frequently in their applications such as Chatbots.

The development of LLM presents additional perspectives of different fields across the diversification of knowledge and lifestyles, with additional prospects for innovation, experimentation, knowledge acquisition, and across domains like research, finance, health care, etc. Thus, the utilization of NLP and AI, these models significantly transformed our engagement with the machines. Therefore, we can see the evolution of LLMs across the different research and commercial

organizations with different names such as Brad, LLaMA, Falcon, Claude, Guerilla, etc. (Hadi et al., 2023).

According to a study by Giglietto (2024), OpenAI embeddings appear to be better than BERT embeddings. However, this finding is not entirely conclusive for English text, as the study was conducted primarily on Italian text. The reason we used OpenAI embeddings instead of BERT is that it demonstrates superior performance all across the benchmarks, particularly for our specific usage.
If we refer to the MTEB Leaderboard (Massive Text Embedding Benchmark), which aims to assess the quality of embeddings, there is a long and comprehensive list of embedding models.

As we know, embedding models start with text and convert it to numbers. All models do the same, converting text to numerical output. To determine which one is better, they run a standard battery of texts. However, stating that one embedding model is better than others is complex, as it depends on a case-by-case basis. For example, in the "Performance by Task" section, we can observe tasks performed by different models. Clustering is also included, showing which model provides better clustering. Accordingly, in this performed task, OpenAI appears better. This text is run for different languages as well, but the main text is in English. Using English, it seems that OpenAI is better than others. According to this benchmark, which is performed through a standard text, it is thus limited.

Here, we know that the BERT model seems to get a worse score in terms of clustering tasks compared to OpenAI embeddings. Through this demonstration, OpenAI is presented as better, and we prefer it over BERT.
Moreover, if we look into the discussion for Task-Specific Considerations, carried out by Open AI developer community and they noted if the task is semantic textual similarity (STS), their posts showed mixed results with Ada 002 having higher Pearson correlation (0.8337), compared to BERT models (0.76-0.79), suggesting better performance in some metrics (BERT better than Ada 002? - API, 2023).

3.5 Integration of LLM with Academic Research

With the integration of LLM models, Researchers have successfully applied Artificial Intelligence (AI) tools to conduct and evaluate academic research (Zhao et al., 2023). Colavito et al. (2024) have demonstrated the ability of GPT models to classify issue reports in the absence of labeled data. Holmes et al. (2023) introduced the concept of using large language models (LLMs) to re-label structure names to establish a benchmark for future studies to reference in Medicine. S. Zhang et al. (2024) presented a unique framework for Automated Molecular Concept (AutoMolCo) to generate and labeling for each molecule because of the leverage of Large Language Models (LLMs). Yu et al. (2024) tried to employ the affordances of GPT4 and Copilot to automate the annotation process by using natural language promptings and focused on abstracts from articles in four applied linguistics journals.

This part of the study focuses on the exposure to the dynamics and interaction pattern of COVID-19 content on Facebook during the initial period of the pandemic in India. With the capability of LLMs to deepen our understanding of the pandemic related information and awareness are shared or spread through the interactions of people in the Context of India. Employing data sources from multiple media outlets, our approach is to classify the pandemic-related posts, make them clustered, generate descriptive labels for those clusters, and get leverage of the advancement of LLMs' advanced natural processing capabilities.

Our concept of methodological part is based on three distinct ways:

1. Model fine-tuning to build up a reliable unilingual classifier of COVID-19-related and non-related posts in English languages.
2. LLM-based embedding for clustering-related and similar posts
3. Direct approach with API to create a short but descriptive label for the cluster Identification.

Chapter 4: Data and Methodology

This chapter brings together the data collection, preprocessing, and other analytical methods that are employed for this study to investigate the COVID-19 pandemic news coverage and the public reactions to Facebook in India.

Here, we took advantage of different methodological approaches to carry out the analysis and results; these are the combination of time series analysis, embedding-based topic modeling, GPT-4 assisted cluster labeling, and sentiment analysis to provide a comprehensive understanding of the information ecosystem of Facebook during the COVID-19 pandemic with emphasis on the early stages of the pandemic.

The four selected newspapers which are The Times of India, The Indian Express, The Hindu, and Hindustan Times - for the study are based on their long-standing history and reputation for credible journalism and their diverse readership and wide geographical reach. First, The Times of India was founded in 1838. It is one of the oldest newspapers and has emerged as the world's most widely circulated English daily (The Times of India, n.d.-a). It has the largest circulation among all English dailies, with populist appeal among urban and semi-urban middle-class readers (The Times of India, n.d.-b; Tripathi, 2025).

The Indian Express was established in 1932 and is renowned for investigative journalism with resistance to censorship, particularly during India's Emergency period (1975–1977) ("A Blank Editorial," 2018). It appeals to urban intellectuals with editions for cities like Mumbai and Delhi (Why Indian Express, n.d.)

The Hindu was established in 1878 and is famous for progressive editorial and balanced reporting, referred to as "the conscience of India" ("About Us-The Hindu," n.d.). The Hindu is the most influential newspaper in South India and appeals to educated and policy-oriented readers ("The Hindu Is the Undisputed #1 English Daily in South India," 2018).

Lastly, Hindustan Times, founded in 1924, played an important role in the Indian freedom movement and has remained a dominant player in North India ("1924-1935: The Early Years," 2024), especially Delhi-NCR, targeting professionals and cosmopolitan audiences ("First Voice Last Word," n.d.)

During the COVID-19 pandemic, digital platforms became crucial for accessing news and information due to disruptions in printing and distribution of print media caused by lockdowns and public health concerns about virus transmission through physical newspapers. Ninan (2021) also highlighted the significant disruptions in the Indian newspaper industry faced during the pandemic crisis.

Whereas all news outlets have a robust presence on social media, making their coverage more widely available, The Times of India's website reportedly had a flexible paywall during peak pandemic months by offering its digital platforms (Ninan, 2021). The other three news outlets i.e. The Hindu, The Indian Express, and Hindustan Times - also extended their digital reach and offerings. E-papers, mobile apps, and social media engagement ensured they remained key sources of information (Mudit & Shamika, 2021). On Facebook, The Times of India leads with 11 million followers (The Times of India, n.d.), followed by The Indian Express with 7.5 million (The Indian Express, n.d.) and Hindustan Times with 7.2 million (Hindustan Times, n.d.) Whereas The Hindu has 5.3 million followers (The Hindu, n.d.).

Using the main four news outlets for the COVID-19 study, the news coverage is a strategic choice to enhance the validity and depth of the research. If we consider editorial diversity and target audiences, it leads to a broader variation of news and themes. Different news outlets may focus on different aspects of COVID-19-related news; these thematic variations allow for a more comprehensive analysis of public opinion on different topics.

Thus, by including multiple media outlets, our analysis captures a wide range of perspectives on the ongoing COVID-19 pandemic. That is important for knowing how the different narratives shape the sentiment and engagement of the public. Media diversity is considered for healthy democratic discourse, and it allows many views to represent them (Deacon & Stanyer, 2021).

Analyzing the posts derived from four media outlets increases the volume of data for the computational methods i.e. sentiment analysis and topic modeling. A large dataset can enhance the reliability and validity of findings and allow more feasibility for statistical analysis such as Analysis of Variance (ANOVA) by which it would be easy to assess the user reactions across the different thematic clusters (Macnamara, 2005; Neuendorf, 2002).

Utilization of multiple resources allows the cross-validation of the findings as well. If the same themes or sentiments emerge across different news outlets can strengthen the credibility of the result. That approach is fit with practice for content analysis where triangulation of sources is recommended to mitigate the bias and enhance reliability (Lynch & Peer, 2002). The general perception is that each newspaper or media group may have a bias due to their affiliation with a political party and ideology or commercial interests.

Including multiple media outlets, would counterbalance these biases by providing a more holistic view of media coverage during the crisis of COVID-19, thus media diversity always holds a prominent place in research (Ciampaglia et al., 2018; Loecherbach et al., 2020).

4.1 CrowdTangle and Facebook Data

CrowdTangle is a tool owned by Meta, the parent company of Facebook that tracks interactions for Facebook groups, public profiles, pages, and verified accounts (Tess, 2022). The verified researchers were allowed to query Meta's databases through this tool.

4.1.1 Data Collection

We use CrowdTangle for its Historical Data and search feature using the following: parameters: Keyword = COVID-19*; Platform = Facebook; Account Type = Pages; **Timeframe = March 24, 2020 - March 31, 2022**; Post Type = All Posts; Language = English, List =The Times of India, The Hindu, Indian Express, and Hindustan Times (all manage and maintain by the CrowdTangle team) and keep other settings on default.

This query yielded Facebook posts that received a total of 68319 posts with interactions from Facebook users. Each post corresponds to a news article shared by the mass media outlet, which backs to the complete articles hosted on their respective websites.

Another subset for **Timeframe = March 24, 2020 -April 14, 2020 (22 Days)**; received a total of 8622 posts.

* COVID-19-related Synonyms with the combination of different key phrases and Boolean operators.

4.1.2 Data Cleaning and Pre-processing

The first move is to Data clean and preprocess for further steps, this raw data needs to be processed through many steps, like the removal of non-textual elements (HTML, Other types of Tags, special characters); language detection to ensure it would be in English only.

4.2 Time Series Analysis

Parzen (1961) defined a time series as "a set of observations arranged chronologically" (p. 951). It is a powerful method to analyze sequential data over time. In social media research, time series analysis gives researchers the opportunity to identify patterns, trends, and unusual events in user engagement data.

Time series is considered the cornerstone of modern statistical modeling, with applications spanning many fields including economics, engineering, environmental science, and public health. Its core lies in the distinction between stationary and nonstationary models. The critical distinguishing characteristics of both models determine the choice of analytical techniques, the validity of inferences and the accuracy of forecasting.

The stationary modeling process is characterized by stable statistical properties over time, which enable robust and reliable parameter estimation and predictions. The time series is considered under the classification as strictly stationary if its joint probability distribution remains invariant under temporal shifts, meaning statistical properties such as mean, variance, and autocorrelation are time-independent (Hamilton, 1994).

This strict regulation is often relaxed to weak stationarity, where only the requirement is a constant mean and autocovariance over time, which permits certain forms of heteroskedasticity. For example, financial returns might exhibit weak stationarity with constant average returns but time-varying volatility; models like GARCH (Generalized Autoregressive Conditional Heteroskedasticity) capture these clustering effects (Shumway & Stoffer, 2025).

For stationarity, its practical implications are profound. In the field of econometrics, a stationary consumer price index allows managers to disentangle transient shocks from persistent inflationary trends. For the Box–Jenkins methodology, stationarity is a critical precondition for effective implementation of ARIMA (Autoregressive Integrated Moving Average) modeling, as applying

the model to nonstationary data can result in spurious correlations and unreliable or biased parameter estimates.

On the other hand, nonstationary models accommodate evolving trends and structural breaks, which are important for analyzing data characterized by volatilities, cyclical patterns, and shifting means (Box et al., 2015; Hamilton, 1994). Nonstationary GDP data often exhibit upward trends that require differencing or detrending before applying autoregressive models (Box et al., 2015).

Non-stationarity presents three primary mechanisms: trends, seasonality, and structural breaks. Determination of trends, such as linear growth in particular data, introduces means depending on time, while stochastic trends arising from unit roots generate cumulative shocks that can permanently alter the series trajectory (Dickey & Fuller, 1979).

For seasonal non-stationarity, as observed in monthly electric consumption patterns; to analyze these patterns more accurately, we used methods like seasonal differencing or Fourier-based decomposition for separating repeating cycles. Structural breaks like abrupt policy changes during economic crises can create regime shifts that may violate stationarity assumptions and demand adaptive models or intervention analysis (Priestley & Rao, 1969).

It is crucial to distinguish between deterministic and stochastic trends. A series with a deterministic trend can be made stationary by removing a time-dependent function, but a series with stochastic trends requires differencing to eliminate unit roots and make it stationary. For example, a random walk process contains a stochastic trend (Hamilton, 1994).

The ARIMA(p,d,q) model is based on ARMA processes by including differencing of order d to handle nonstationary data (Box et al., 2015). If d is greater than 0, then ARIMA can be used for nonstationary time series; on the other hand, if d is 0, it reduces to the standard stationary ARMA model. Parameter selection for the right model using AIC or BIC should consider the

impact of differencing. Using too much differencing can lead to too many moving average (MA) terms and poor out-of-sample forecasts (Hamilton, 1994).

On the other hand, ARFIMA (fractionally integrated ARMA) models allow d to be a non-integer, capturing long-term dependencies in time series, such as in hydrology where the effects of past events fade slowly over time (Shumway & Stoffer, 2025). However, ARFIMA models are more complex to estimate and need careful validation of persistence parameters.

Social media gives opportunities for timeline mining, whereas social media also gives opportunities for every user to create and share information about an entity in any place at any time, and it becomes rich historical data (Wang et al., 2021). It is proven that analyzing the time series of niche social media has a significant value for key narratives (Skumanich & Kim, 2024), recognized and utilized for determining causation in agenda-setting studies as well (Meraz, 2011). Here, we used Time series analysis techniques to identify unusual patterns and suddenly changed for "Facebook reactions" over a certain period. Here we employed two methods to know i.e. Percentage change method and the Z-score method with rolling statistics.

For executing this analytical part, we used R language together with different libraries Such as library(dplyr), library(ggplot2), library(zoo), library(readr), library(lubridate), and library(scales).

The combination of two methods was implemented in the R script for detecting the unusual days and sudden changes in the Facebook reaction data, during the period of the chosen timeframe.

4.2.1 Percentage Change Method

Here, day-to-day percentage changes are calculated. The days with percentage changes in the top 5% (95th percentile) are pointed out as unusual.

For Calculation: ((Current day's count - Previous day's count) / Previous day's count) * 100

In general, this method we used to calculate the day-to-day percentage change in reaction counts.

It is suggested that capturing the sudden spikes or drops in engagement and, the relative measure allows the comparison across different scales of engagement. It is effective for the identification of short-term, dramatic changes, thus useful to know if there is viral content or significant events be there that cause a rapid increase or decrease in reactions.

4.2.2 Z-score Method with Rolling Statistics

The Z-score method employs a 7-day rolling means and standard deviations for identifying the anomalous patterns in the data. The Z-score calculation is computed (for each day) by this formula:

Z-score = (Day's count - 7-day rolling mean) / 7-day rolling standard deviation

Days with a threshold where Z-scores greater than 2 are flagged as unusual, representing significant deviation from the established pattern. This method excels at incorporating both recent data trends and cyclical or seasonality patterns; and identifies the deviations of the outliers from typical recent behavior. The strength of the Z-score technique is its ability to detect the subtle yet meaningful shifts in the data while automatically adapting to changing baselines over time, which is crucial for longitudinal data analysis.

For the analytical process, we implemented a 7-day rolling window technique to quantify how many standard deviations a day's count differed from the recent mean.

The fundamental analytical steps we performed are described below with the relevant R code.

First, we computed the rolling mean and standard deviation for reaction counts using a 7-day window:

```
# Calculate rolling mean and standard deviation
data$rolling_mean <- rollmean(data$reaction_count, k = 7,
                              fill = NA, align = "right")
data$rolling_sd <- rollapply(data$reaction_count, width = 7,
                             FUN = sd, fill = NA, align = "right")
```

Here, the rolling mean was calculated using the window size of 7 days, providing a weekly average of reaction counts:

```
data$rolling_mean <- rollmean(data$reaction_count, k = 7,
fill = NA, align = "right")
```

Similarly, the rolling standard deviation was determined by the same 7-day window to capture the variability in reaction counts:

```
data$rolling_sd <- rollapply(data$reaction_count, width = 7,
FUN = sd, fill = NA, align = "right")
```

Here, the functions rollmean() and rollapply() from the zoo package are used for computing rolling calculations on time series data. Moreover, their functionalities and arguments can be understood as follows: rollmean() computes rolling means, maximums, medians, and sums and is optimized for speed, similar to rollapply(); whereas rollapply() is a generic function that applies a specified function to rolling margins of an array.

The key arguments in these functions: data – representing a series of observations; width/k, specifying the number of points in each group or the window size; FUN, the function to be applied for each rolling window (only in rollapply()); fill, determines the values to fill the initial positions where a complete window is unavailable, with fill = NA resulting in missing values for these positions; align, specifying the alignment of the result relative to the rolling window, where align = "right" ensures each computed value represents the statistics for the preceding window, useful for understanding trends over time; na.rm, a logical argument that removes NA values; and partial, which, if TRUE, allows the function to be calculated even for windows with fewer than width observations.

Next, we calculated the Z-scores by comparing how each daily count to its recent statistical context (rolling statistics). The following formula is for the z-score:

$$Z = \frac{X - \mu}{\sigma}$$

Whereas:
X is the actual reaction count,
μ is the rolling mean (7-day average),
σ is the rolling standard deviation (7-day variability).

```
# Calculate z-scores
data$z_score <- (data$reaction_count - data$rolling_mean) / data$rolling_sd
```

Finally, we detected unusual days using both a Z-score threshold and a supplementary percentage variation threshold as a secondary filter:

```
# Identify unusual days
z_score_threshold <- 2
pct_change_threshold <- quantile(abs(data$pct_change), 0.95, na.rm = TRUE)
data$unusual <- abs(data$z_score) > z_score_threshold |
            abs(data$pct_change) > pct_change_threshold
```

For the detection of significant fluctuations in user engagement, unusual days were identified based on two major statistical measurements i.e. z-scores and percentage change in reactions.

Here, the Z-score threshold is considered as a rection count was unusual if its Z-score got exceeded a predefined threshold (2); this threshold is an indicator for the reaction count deviated by more than two standard deviations from the rolling mean, that highlights anomalies.

For the percentage change threshold, sudden spikes or drops in engagement might not always be captured by the Z-score alone. Therefore, the 95th percentile of absolute percentage changes was used as an additional criterion. Any reaction count with a percentage change exceeding that threshold would be extreme shifts in engagement patterns and flagged as unusual.

We used these methods because of their comparative approaches, the percentage change methods catch short-term, sudden changes while the z-score method identifies in the context of the trends; by using these, both provide a comprehensive view of the “Unusual” behavior/activity. If we talk about their adaptability social media engagement can be flexible over the period. These methods are used to change the baseline and make them suitable to analyze longer periods, here in this case 2020-03-24 to 2022-03-31.
By using the rolling statistics for z-scores the analysis considers the recent context for each data point, which is too important in the context of rapid changes in social media and news.

Both methods provide a quantifiable approach that provides clear, numeric thresholds for the “unusual” days, and allow for consistent analysis across the different reaction types and news outlets. These methods are suitable for time series data for Facebook reactions because they capture longer-term trends and day-to-day volatility in both ways.

They are more flexible, the thresholds (z-score > 2, top 5% of changes) can be adjusted, based on how sensitive or specific the analysis is to be needed. It is considered non-parametric because these methods do not assume a particular distribution of the data, making them robust for various patterns of social-media engagement. The complete R code implementation for both the percentage change method and Z-score method is provided in Appendix B.

Thus, with the combination of those two methods we can analyze effectively and identify the “Unusual” days and engagement, whether due to gradual shifts in audience behaviors, sudden viral contents, or significant news/events that provide valuable insight into the dynamics of Facebook reactions to news post/content over the time.

Here in this stage, we have the data derived by CrowdTangle. Then, the first move is to Data clean and preprocesses for further steps, this raw data needs to be processed through many steps, like removal of non-textual elements (HTML, Other types of Tags, special characters); language detection to ensure it would be in English only; Tokenization and lemmatization for English language and then removal of stop and low-frequency terms.

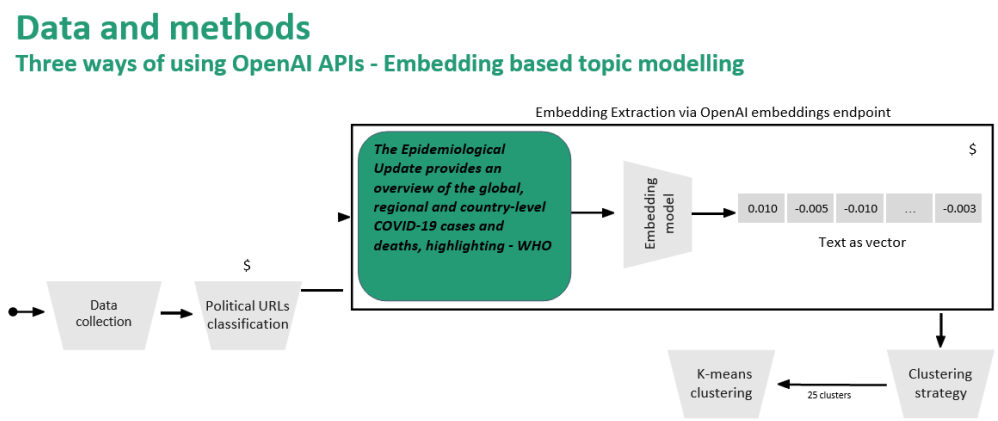

Figure 1 - *The Large Language Models Turning Point for Media Scholars. Courtesy of Giglietto (2024).*

4.3 Embedding-based Topic Modeling Using OpenAI APIs

Once we identify the posts/links related to COVID-19, the next step would be to transform them into embeddings. The embedding is a numerical representation of the semantic content of the link/post; through this, it facilitates the clustering process (please refer to Figure 1). This process can use different types of LLM-based embedding models. Ultimately, we selected OpenAI's text-embedding-3-large model, which was based on the metrics of the silhouette score.

4.3.1 Vector Representation

For transforming the textual data to further input for machine learning analysis, we need to use the embedding API of Open AI for employing the Text embedding model. In this model, every textual input i.e., Title, content, or description turned into dimensional vectors. The purpose is to capture the semantic relationship with the words.

4.3.2 Clustering Analysis

Selection of Algorithm and Implementation- we have identified the K-means clustering algorithm for the embedding vectors that are suitable to identify the distinctive themes within the laid dataset of COVID-19 combined News outlets. The choice behind the selection of K-means was based on its efficiency with high-dimensional data for large datasets.

For this, we implemented the algorithm by using the package (Rtsne) for the R language. Now obtaining the cluster we employed the Silhouette analysis to find out how similar an objective is to other clusters and to compare within our cluster. Based on this analysis we got twenty-five distinctive clusters. Then we run the Principal Component Analysis **(**PCA) setting for large matrices of 8096 data.

4.3.3 Dimensionality Reduction and Visualization

t-SNE (t-Distributed Stochastic Neighbor Embedding) is a dimensionality reduction technique used for visualizing high-dimensional data. It converts similarities between data points into joint probabilities and aims to minimize the divergence between the joint probabilities of the low-dimensional embedding and the high-dimensional data. In this study, we employed t-SNE to reduce our high-dimensional embeddings into a two-dimensional (2D) representation, making it possible to visualize and interpret the relationships between different news articles and their associated themes more effectively.

This implementation of t-DSN was carried out through the R Package Rtsne within the parameter of - Perplexity: 30, Number of iterations: 1000, and finally, t-SNE dimensionality reduction was completed. Please find Figure-1 for K-means clusters below, what we carried – The K-means clustering visualization is presented in Appendix C, Figure 1.

4.3.4 GPT-4 Assisted Cluster Labelling

We employed GPT-4-0125-preview, a large language model developed by OpenAI as part of its GPT-4 Turbo series, on January 25, 2024 (Basheer, 2024). It operates with a context window capacity of 128,000 tokens and maximum output generation of 4,096 tokens per interaction (Telnyx, 2024). This iteration incorporated many important improvements over its predecessor, i.e., GPT-4-1106-preview. Microsoft (2025) documented this model as having "higher accuracy at responding in requested formats and a fix for a bug which caused a text encoding issue". This model achieved the LMSys Arena Elo Score of 1245 and a 76.5% success rate on the HumanEval benchmark, indicating robust capability across multiple metrics for its performance (Portkey, 2024). (The complete implementation code for embedding generation is documented in Appendix C).

We developed a unique method to employ the GPT-4 language model (OpenAI's API) for cluster labeling. For this process to be carried out we go through many steps to get Clusters labeled.

a) Prompt Engineering- We developed the Prompt which is based on COVID-19 queries within the context of India. It had been refined till the output came out with the relevancy of query design.
b) Cluster Sampling- for each cluster, we fed a few representative samples of URLs to ensure the balance between the sample size and APT token limits.
c) Label Generation- Finally, the label was generated by using the above process and it was the chat completion endpoint. We got a model-generated full concise descriptive label for every cluster.
d) Label Validation- for the validity and to ensure this output, we used a manual check-up to ensure every label is accordingly fit for its own.

4.4 Sentiment Analysis

We used novel models for embedding and labeling of clusters but then reverted to Natural Language Processing techniques for sentiment analysis, which is a well-established and validated approach, despite the fact that this analysis could be performed using GPT-4. When we designed the pipeline based on novel approaches, these methods were not thoroughly tested for sentiment analysis. It would be better to use well-known and established metrics, which might be older but are proven and reliable in this field.

Moreover, studies conducted by Catelli et al. (2022) and Islam et al. (2024) argued that this technique is helpful when the dataset is small. As these studies show, lexicon-based approaches can still perform well based on the results obtained (Catelli et al., 2022). Our dataset is not huge, so we prefer to use this technique under these conditions as well. If we consider domain-specific adaptability, it is another advantage. For example, the study conducted by Jurek et al. (2015) focused on real-time Twitter analysis, demonstrating that lexicon-based approaches can utilize domain-specific dictionaries, enhancing effectiveness and performance for niche areas where general models often face challenges.

We already have a labeled clustered dataset. Now, to get the sentiment and emotional response of users toward COVID-19 news posts, and to perform the sentiment analysis to know the user sentiment score, we use a lexicon-based Sentiment analysis based on the R package named “sentimentr”.

4.4.1 Lexicon-based Sentiment Analysis Using the Sentimentr Package

The R package named “sentimentr”, is designed to calculate text polarity sentiment for English at any sentence level and can aggregate with the rows or grouping variables, (Rinker, 2015/2024). Employing the ‘sentimentr’ package for analyzing sentiment during COVID-19 for Facebook posts provides many advantages. It is designed to balance accuracy and speed with valance shifters

such as negators, amplifiers, de-amplifiers, and adversative conjunctions. Valence shifter can alter the sentiment of sentences, for instance - a negator like "not" can flip the sentiment of a word (e.g., "not happy" vs. "happy"), thus these shifters provide accurate sentiment analysis as well, and in sentence-level analysis (*Sentimentr Package - RDocumentation*, 2021), this package ensures that sentiment analysis would more accurate and precisely compare to dictionary look-ups….it is also giving advantage as optional aggregation by rows or grouping variables, making it easier to analyze sentiment trends over time or across different user groups (*Sentimentr Package - RDocumentation*, 2021). For these reasons 'sentimentr' became an effective tool for conducting analysis (Hellín et al., 2023).

Moreover, the feature includes handling of mixed sentiments, sentence-level analysis with a lexicon-based approach, robustness across datasets, and seamless integration with other R tools to enhance the efficiency of its performance (Rinker, 2016).

4.4.2 User Engagement Matrix and Sentiment Scores

By using this sentiment package, the researchers can systematically analyze sentiment expressions in Facebook posts, providing valuable insights into public reactions to COVID-19 pandemic events such as lockdowns and vaccination campaigns (Chandra & Krishna, 2021). We leveraged these functionalities of the sentiment package by linking the 'Facebook reactions' with the associated 'messages' to perform sentiment analysis on the textual content.

Sentiment Calculation: -

Calculate sentiment scores using sentimentr package sentiment_score = sapply(message, function(x) sentiment_by(x)$ave_sentiment),

In the context of News articles, “Facebook reactions” play a significant role in understanding Users' sentiment toward the posts or articles. In setting up of User-Engagement Matrix these “Facebook Reactions” (love, wow, haha, sad, angry) indicate emotional responses to the posts or articles. Here, we find an aggregated to form a user_reaction score. Whereas Sentiment Score, the layered cover represents the sentiment as positive, neutral, or negative, conveyed in the textual content of the posts.

Aggregate Facebook reactions to create a user engagement score user_reaction = statistics.actual.loveCount + statistics.actual.wowCount + statistics.actual.hahaCount - statistics.actual.sadCount - statistics.actual.angryCount)

The calculated sentiment score (sentiment_score) is used for statistical and ANOVA analysis for a better understanding of the sentiment distribution across all the clusters and other news outlets. By analyzing both the sentiment score (sentiment_score) and user_reaction score, we explored the relationship in-between the Texts and what/how the users’ reactions were to them.

Then created visualizations to better understand the relationships between sentiment scores and user reactions in different aspects.

We prepared the data for this step for each News outlet with their story counting within each cluster with the consideration of five unique “Facebook reactions”.

After running the R script, we analyze:

A) We calculated the sentiment score and user reactions for each post,
B) Then, summarize the statistical summary for the average sentiment score, average user reaction, and story count, for every cluster,
C) Calculate the correlation in-between the average sentiment score and user reactions across all clusters,
D) Calculate the sentiment score for each cluster separately.

We drew the margin of error and then carried out the residual outliers and their clusters. And then analyze the content of clusters of interest.

Chapter 5: Results and Analysis

This chapter presents a comprehensive analysis of how Indian audiences engaged with COVID-19 news content through "Facebook Reactions" across four news outlets on Facebook during the pandemic period from March 24, 2020, to March 31, 2022. As discussed previously, "Facebook Reactions" buttons enabled users to express more nuanced emotional responses to content on Facebook. Here, user interaction was measured through "Facebook Reactions" on pandemic-related posts.

Our analysis revealed that users applied different reactions strategically to express their emotions on different types of COVID-19-related news. For example, "Love" reactions were mostly used for "community support" and "healthcare workers," whereas "Angry" reactions were frequently used on posts about lockdown violations or controversial policies. "Haha" reactions often appeared on posts related to lockdown life, unique adaptations, or government announcements, and "Sad" reactions were used for COVID-19 casualties and migrant worker crises.

The data analysis is comprised of three major sections:

First, we present a detailed time series analysis of Facebook reactions, which examines the pattern of emotional engagement throughout a certain period of the pandemic. This includes identifying unusual spikes in specific reactions and analyzing which types of content elicited strong emotional responses from users.

Second, we conducted topic modeling and cluster analysis and explored the results, which revealed 25 distinct thematic clusters for COVID-19-related news coverage. We found that each cluster had unique patterns of user interactions through different "Facebook Reactions" types when engaging with specific topics.

In the third part, we examined sentiment analysis to reveal how the emotional tone of users correlated with news content and user engagement through reactions. This study provides insights into how different news outlets covered users' emotional responses.

5.1 Time Series Analysis of Facebook Reactions

The time series analysis for total interactions over time presents an overall view of total interactions for the four media news outlets, rather than monthly or weekly views. The "interactions" appear to be measuring user engagement with these news outlets' content on Facebook. The y-axis shows the total number of interactions, which includes the total number of "Facebook reactions" used by users on posts.

Interactions range from 0 to about 150,000 at their peak. The highest spike occurred early in 2020. The Times of India reached approximately 150,000 interactions. After that, the interactions generally decreased over time, with occasional spikes.

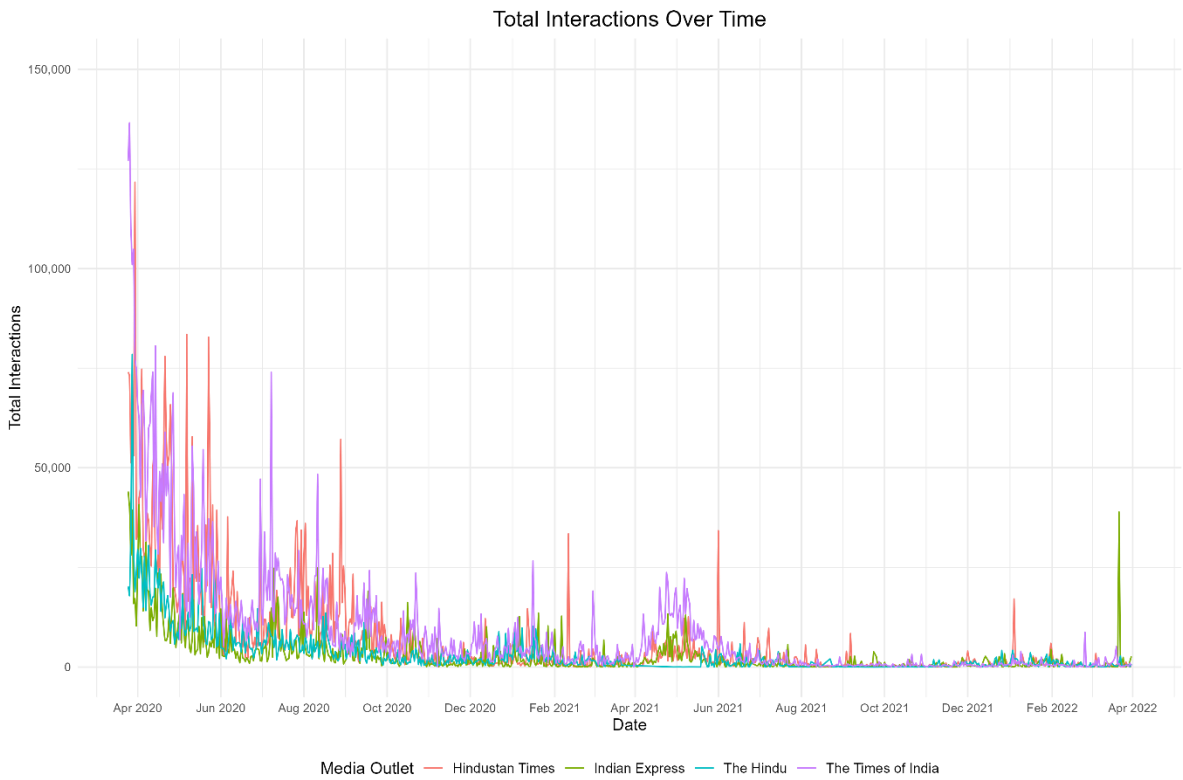

Figure 2 - *Total Interactions Over Time*

It confirms a massive spike in interactions between March and April 2020, which corresponds to the onset of the pandemic COVID-19. The key observations are easily understood after the initial spike. There are many similar spikes throughout the timeframe for various accounts/outlets. The data appears

more volatile daily compared to weekly or monthly engagement. Whereas the overall trends show that interaction level decreases over time with occasional spikes. There is a notable spike for the Indian Express news outlet for the end of the timeline, earlier 2022.

5.1.1 Overall Trends and Patterns

For monthly total interactions, the four major news outlets show on Facebook from early 2020 to early 2022. The total interactions show 1,500,000, with tick marks for every 6 months (2020-07, 2021-01, 2021-07, 2022-01).

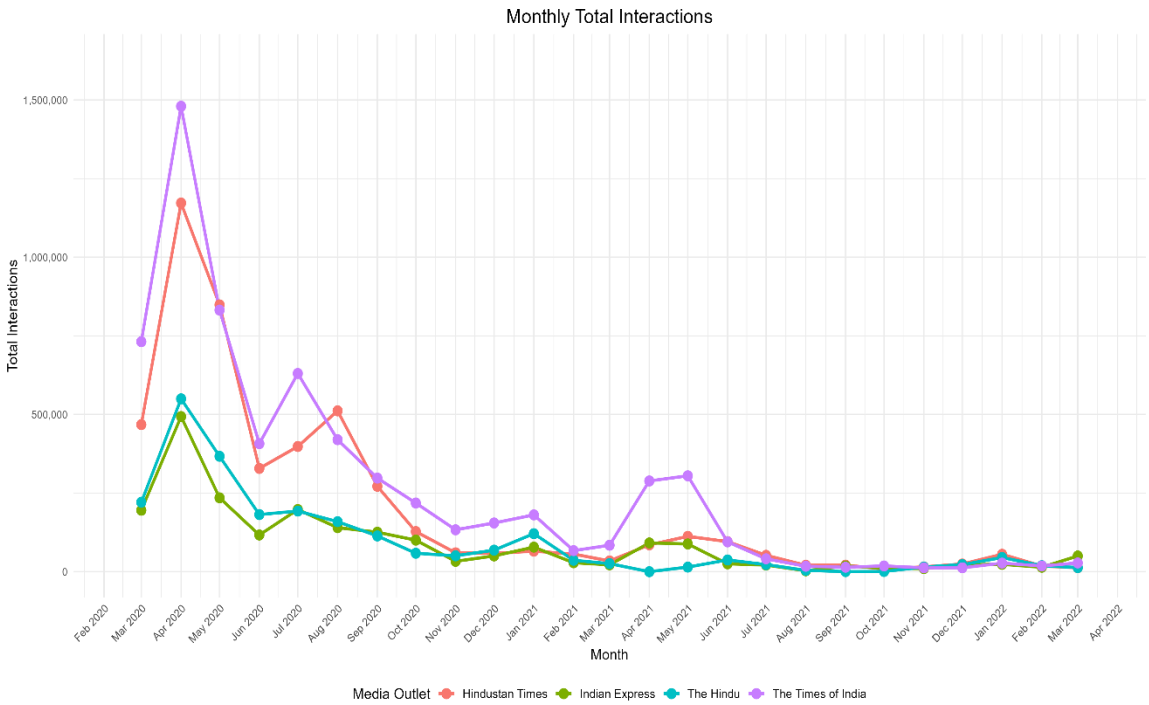

Figure 3 - *Monthly Total Interaction*

In initially. All four news outlets show a major spike in interaction for March and April 2020. This co-incident shows the onset of COVID-19 and subsequently lockdowns imposed in India. Here The Times of India caught up with the highest peak nearly 1,479,192 total interactions, the highest among all outlets, followed by Hindustan Times closely with 1,172,104 interactions in

April 2020. The Hindu came third in total interactions and had a peak in April 2020 with total interactions of 549,664. Whereas, Indian Express had the lowest total interactions among all four. Its peak was in April 2020, with total interactions of 493,936.

By the end of the period, the interaction for all major news outlets decreased to below 250,000 per month but followed similar trends.

These spikes are likely the representation of an unprecedented surge in COVID-19-related news and interaction with Facebook reactions by users.
We can notice there is a gradual decline after the initial spike. There is a shaping trend to decline followed by a gradual decline in the interactions for all major news outlets. It could be the indication of news consumption with the users tend to normalize the pandemic.

In the timeline, we can observe many smaller surges, the spikes are visible throughout, The Time of India. These periodic surges could be represented by major events, COVID-19 smaller waves. Or other developments in India.
If we consider the news outlets' performance, The Times of India has consistently maintained the highest level of interactions throughout the period. Hindustan Times is closely leg behind The Times of India. Whereas The Hindu and Indian Express generally get the lower but similar trend of interaction of trends.

By the end of the timeline, late 2021 to earlier 2022 the interaction levels for all news outlets converge to much lower. This convergence indicates fatigue from the pandemic and its related news consumption and their interactions, the shift of the users to fewer interactions on Facebook.

Notably different Facebook reactions, and “Haha” reactions are most commonly found all across news outlets, especially for The Times of India and Hindustan Times. “Angry” and “Sad” reactions were significantly placed during the early months of the COVID-19 pandemic, especially in March-April 2020. “Angry”

reaction spikes up in March and April 2020 significantly. "Wow," reaction is generally the lowest used among all of them.

For engagement distribution for reactions, The Times of India has consistently for “Haha” reactions about 30-40% of its total interactions. The even distribution of reactions has been seen in Hindustan Times. Compared to the other two news outlets, The Hindu and Indian Express have higher proportions of “Sad” and “Angry” reactions than the two news outlets.

The distribution of Skew, where all metrics the mean is significantly higher than the median shows a right skewed distribution. It suggests that most posts received moderate engagement. Some posts got exceptionally high engagement and pulled the average up.

The engagement variability in post-performance for each metric, e.g., 0 to 14,632 for Angry reactions shows that some posts go viral or become controversial by nature while others get minimum engagements.
The total interaction maximum (136,493) compared to the median (1,640) shows the potentiality of posts to be viral, achieving an engagement level of 80 times the typical post.

For engagement Levels, in the 1st quartile, 25% of posts receive fewer than 423 total interactions. While fifty percent of posts receive between 423 and 5,870 total interactions and 25% of posts receive more than 5,870 total interactions in the 3rd quartile.

The highest median and mean are for “Haha” reactions, and it is the most common reaction. “Wow” reaction is the least common among those listed, whereas “Love” (167) and “Sad” (166.6) reactions have the same mean values but different medians, which suggest different patterns of distribution.

If we talk about the weekly trends for those four news outlets together, they provide insight into the weekly total interaction trends. Here, for five weeks in March and April 2020 shows various interaction types i.e. Love, Haha, Wow,

Angry, Sad, and the total interactions for all four news outlets i.e. Hindustan Times, Indian Express, The Hindu, and The Times of India. The below graph presents a longer-term view of weekly total interaction trends from early 2020 to early 2022 for those news outlets.

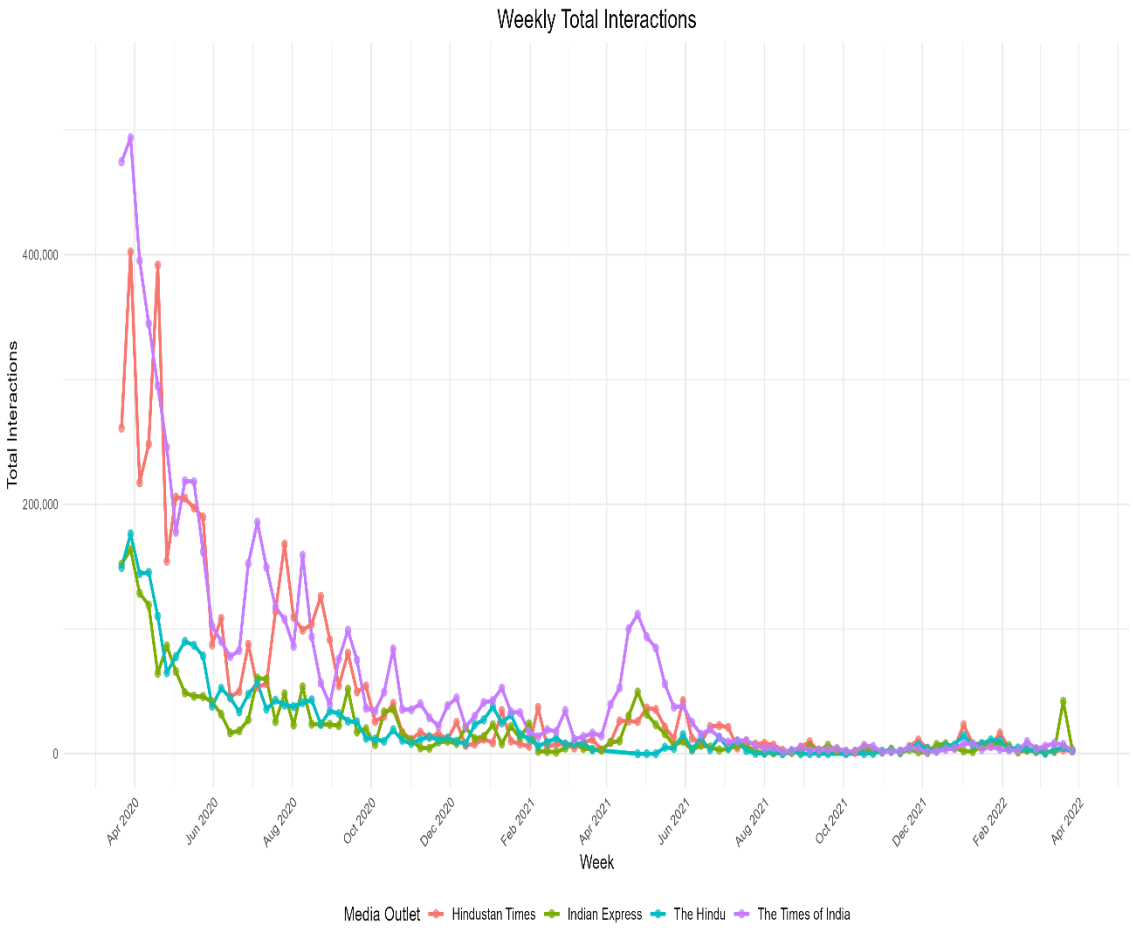

Figure 4 - *weekly Total Interactions*

In the beginning, it shows the initial spike and significant interactions for all four outlets in late March 2020. It is likely to correspond the starting point of COVID-19 with the association of lockdown in India.

The trend over time shows a clear downward trend for the total interaction for all major news outlets. The interaction level gradually decreased and stabilized by early 2021 at a much lower level.

Here, The Times of India continued to have the highest number of total interactions which picked up nearly 496,306 interactions (week of March 29, 2020). Whereas Hindustan Times gets the second most engaged with a peak of around 400,306 interactions (week of March 29, 2020), followed by The Hindu and Indian Express. But they get similar levels of user engagement, mostly falling between 100,000-200,000 interactions at their peaks. The lowest level of interaction is for Indian Express with 86,439 interactions (week of April 26, 2020). Notably, the week of March 29, 2020, shows the most significant and highest level of engagement for most outlets.

The prevalence of “Haha” reactions with “Love” reactions especially with The Times of India are often too higher than others. “Angry” reactions are also significant trends for a few weeks, particularly with The Times of India in late March 2020.

5.1.2 Unusual Days and Sudden Changes in Reactions for Each News Outlet

The identification of "unusual days" in time series analysis of Facebook reactions represents a critical component for understanding how Indian audiences engaged emotionally during the COVID-19 period and its related news coverage across the four major outlets. We employed two sophisticated methods to analyze the statistical procedure with a combination of z-score analysis and percentage change detection for identifying periods where user engagement deviated significantly from established baselines. These deviations are not only statistical artifacts but represent moments when news content resonated powerfully with users, triggering them to express emotional responses.

This significant identification of unusual patterns extends beyond simple engagement metrics; the spikes in reactions represent moments when Indian Facebook users simultaneously felt compelled to express their emotions about COVID-19 pandemic-related news or information. By analyzing the patterns of the four major news outlets—Hindustan Times, Indian Express, The Hindu, and The Times of India—we were able to map the emotional landscape of COVID-19 and its related news coverage together with the audience, and to understand how different editorial approaches shaped public discourse during the crisis.

Hindustan Times: Navigating Between Information and Entertainment

The Complexity of "Angry" Reactions: Institutional Failures and Public Outrage

For Hindustan Times' pattern of "Angry" reactions gives insight into public frustrations, which included posts related to institutional responses to the pandemic. During the study period, we identified forty-eight days where "Angry" reactions exceeded normal patterns significantly enough to classify as unusual. These did not occur randomly but were concentrated around clusters of specific types of news content that touched the emotions of Indian users.

The most significant example would be seen on January 4, 2022, when a single post achieved 1,709 angry reactions, a remarkable 34,080% increase from the previous day. It was the post where a UK national alleged that Mumbai airport's COVID-19 testing and quarantine protocols constituted a "scam." The magnitude of this response reveals several layers of public sentiment, such as accumulated frustration with perceived corruption and mismanagement, international embarrassment as the involvement of a foreign national added an element of national embarrassment, and economic sensitivity since airport testing fees had been a contentious issue considered exploitative during economic hardship.

Another significant spike is seen in the "Angry" reaction which follows similar patterns. On July 8, 2021, a spike (764 reactions, z-score: 2.27) coincided with reports of the continually ongoing lockdown that would be extended further, despite improving daily conditions for people. On May 17, 2020, a spike (767 reactions, z-score: 2.00) aligned with earlier pandemic health-related measure enforcement that many viewed as heavy-handed. This suggests that Hindustan Times' audience was particularly responsive to stories that highlighted the gap between ground realities and official pandemic management.

"Haha" Reactions: Humor as Pandemic Coping Mechanism

The higher number of unusual days for "Haha" reactions at Hindustan Times, which totaled 66, represents the highest count for any reaction type across all outlets. This highlights a fascinating aspect of pandemic discourse: Indian users frequently employed humor, particularly in sardonic or ironic forms, when engaging with COVID-19 related news. This pattern of engagement deserves detailed examination as it reflects a unique form of public commentary.

There was a significant spike in "Haha" reactions observed on June 30, 2020, where the reactions reached 9,458, which was a 5,886% increase from the previous day. It was the most dramatic surge observed in the whole dataset. This coincided with coverage of government officials making optimistic statements about India's pandemic response during a period of rapidly increasing COVID-19 cases. This ironic use of "Haha" reactions appears to reflect public

skepticism, employing Facebook's reaction feature to express irony or disbelief about official narratives.

Similarly, on July 26, 2020, there was a surge of 6,000 reactions (a 463% increase) that occurred after Prime Minister Modi released his statement that India was in a "much better situation" fighting COVID-19. As this was during India's first wave peak, many users perceived it as unrealistic and expressed their disbelief through "Haha" reactions. This pattern recurred throughout the pandemic. Such as, we can observe that on April 10, 2020, there were 4,354 reactions (a 745% increase) as public responses surged following early lockdown announcements that presented unrealistic optimism. Again, on August 30, 2020, there were 3,579 reactions (a 257% increase)—a significant rise in reactions that coincided with premature "victory" declarations over the virus. Due to confusion over lockdown guidelines, there was a significant rise in reactions on May 4, 2020: 3,366 reactions, representing a 266% increase. This recurring trend suggests that "Haha" reactions may have served as a form of digital protest, enabling users to express dissent through irony rather than direct criticism.

"Love" Reactions: Celebrating Solidarity and Sacrifice

The forty-seven unusual days identified by spikes in "Love" reactions at Hindustan Times tell a parallel story of hope and collective human solidarity during the crisis. These spikes were not randomly distributed but were primarily associated with specific types of content that celebrated kindness and personal sacrifice.

On August 28, 2020, there was a surge of 6,541 "Love" reactions (a 2,548% increase) in response to actor Sonu Sood's promise to help students reach examination centers during the lockdown. This reaction was not simply admiration for a celebrity but recognition of someone using their privilege to address institutional shortcomings. Sood had already gained public attention for arranging transportation for stranded migrant laborers, and this new initiative further established him as a symbol of how a private citizen can step in where government support is lacking. Other significant spikes for "Love" reactions

were observed during the pandemic, and each of them corresponded to specific types of positive content. On May 23, 2020, there was a surge with an increase of 989%, totaling 5,469 reactions, which was associated with stories of healthcare workers' dedication. Similarly, on April 21, 2020, we can observe 4,801 reactions (164% increase) for posts about community kitchen initiatives. Another notable spike for the "Love" reaction occurred on April 12, 2020, with 1,791 reactions (a 186% increase) in response to stories of neighbors helping elderly residents. The highest percentage increase was recorded on June 30, 2021, when posts about the return to normalcy led to 778 reactions, representing a 3,436% surge. The temporal pattern of these spikes indicates that positive engagement remained strong throughout the pandemic, but increasingly extraordinary events were needed to generate unusual response levels as the crisis evolved.

"Sad" Reactions: Collective Grief and Empathy

For Hindustan Times, forty-six unusual days for "Sad" reactions closely reflected the pandemic's human toll. On January 4, 2022, a spike of 1,477 reactions (497.98% increase) occurred on the same day as a major surge of "Angry" reactions but was linked to different content—reports of continued COVID-19 deaths despite widespread vaccination. This simultaneous dual emotional response on the same day suggests that Hindustan Times' diverse content could trigger different emotional responses within its audience simultaneously.

The most compelling and interesting pattern is found during the crisis of the pandemic; it was the peak of the migrant crisis period that also marked the profound emotional impact of pandemic-related tragedies. On April 21, 2020, posts about separated families generated 2,362 reactions, reflecting a 231.74% increase from the previous day. Similarly, August 2, 2020, saw 2,020 reactions (1,736.36% increase) in response to cumulative toll milestones of COVID-19. The most striking instance occurred on October 18, 2020, marking the first significant audience response to this content type, with 1,288 reactions appearing after zero engagement the previous day. These were stories that broke

through the prevailing audience fatigue that had developed over months of pandemic coverage.

"Wow" Reactions: Surprise and Disbelief

Thirty-eight anomalous days for "Wow" reactions emerged at Hindustan Times that often coincided with Facebook posts during the pandemic, illustrating moments of collective surprise or disbelief about the pandemic. For example, on April 25, 2020, a notable spike of 695 reactions (195.74% increase) occurred—an increase from the previous baseline—in response to early reports about the virus's unusual characteristics. Subsequently, the spikes frequently corresponded to scientific breakthroughs or vaccine developments, with the news involving abrupt policy shifts, unexpected epidemiological statistics, or environmental recoveries observed during lockdown. Despite these spikes, the relatively lower numbers for "Wow" reactions compared to other emotions such as anger, humor, or sadness suggest a layered emotional register of public engagement where disbelief played a more episodic than sustained role.

Indian Express: Analytical Depth and Measured Responses

"Angry" Reactions: Focused Frustration with Specific Failures

Across forty-three days, the Indian Express registered a distinct pattern in "Angry" reactions that reveals a more focused and analytical audience response compared to other news outlets. The spikes were less volatile in volume than some counterparts, though they show a clear correlation with specific types of investigative significance. The April 2, 2020, spike of 3,724 reactions (339% increase) corresponded to pointed coverage of religious congregations flouting lockdown protocols. On July 13, 2020, there were 1,923 reactions, a 6,310% increase that seemed modest in absolute numbers but coincided with exposés on politically shielded lockdown violations. Similarly, by December 16, 2021, even a comparatively small spike of 209 reactions (20,800% increase) underscored the rarity of public outrage amid pandemic fatigue.

"Haha" Reactions: Intellectual Irony Over Emotional Response

A notably selective pattern for "Haha" reactions for Indian Express was exhibited with forty-three unusual days that showed anomalous spikes primarily in response to political satire or exposure of absurd policies. On January 2, 2021, a spike of 3,669 reactions (283% surge) responded to Prime Minister Modi's request for Indian Institutes of Management (IIMs) to study India's COVID-19 response. That suggestion was found by many to be ironically discordant amid persisting governance challenges and ongoing crisis management failures. Other notable patterns can be observed on December 19, 2020: 1,629 reactions (239% increase) for bureaucratic confusion, and another spike occurred in response to critical analyses of policy contradictions on August 9, 2020. These examples underscore the sophistication of Indian Express's readership, where the "Haha" reaction often carried deeper satirical meaning rather than simple digital humor.

"Love" Reactions: Appreciating Depth and Humanity

In the course of analysis, Indian Express demonstrated the highest variation among all reaction types, with the "Love" reaction showing anomalous patterns across fifty-one days for this outlet. The most extraordinary surge occurred on October 16, 2020, with an explosion of 2,511 reactions (a 50,120% increase) for a post portraying a migrant mother as the goddess Durga. This response reveals Indian Express's ability to identify a potent cultural metaphor amid pandemic-induced hardships and suffering that could generate overwhelming positive engagement. Additionally, other significant surges in "Love" reactions were seen on August 11, 2020: 1,155 reactions (363.86% increase) for a healthcare hero profile; and on January 6, 2021: 1,083 reactions with a 4,822.73% increase for content related to vaccine development success.

"Sad" Reactions: Sustained Empathy for Human Suffering

Indian Express experienced fifty-three unusual days for the "Sad" reaction. On May 2, 2020, a spike of 1,982 reactions (547.71% increase) coincided with in-depth reporting on overwhelmed crematoriums during pandemic coverage. Again, on September 17, 2020, a surge of 1,931 reactions (2,407.79% increase) followed investigative pieces on undercounted COVID-19 deaths. This pattern suggests that Indian Express persisted through critical phases, with evidence shown on July 12, 2020: 1,871 reactions (95.92% increase) regarding the shortage of oxygen gas, and on May 8, 2021: 1,423 reactions (5,829.17% increase) which covered the analysis of Second wave devastation.

"Wow" Reactions: Revelations Through Investigation

Among forty unusual days marked by elevated "Wow" reactions at Indian Express often followed investigative revelations or exclusive reports. Notably, on October 16, 2020, a significant surge i.e. 327 "Wow" reactions reflecting an 8,075% increase accompanied breaking news about vaccine trials. This trend, characterized by dramatic percentage increases suggests that audience astonishment came from quality of revelation rather than sensationalism.

The Hindu: Consistency, Depth, and Sustained Engagement

"Angry" Reactions: Principled Outrage

The Hindu exhibited distinct engagement patterns for forty-eight unusual days for "Angry" reactions. On April 17, 2020, a spike of 1,870 reactions represented the outlet's highest "Angry" response, triggered by detailed reporting on the Tablighi Jamaat controversy; this reporting stood out with careful attention to avoiding communal overtones. Subsequent surges, including on August 17, 2020, a surge of 689 reactions and September 14, 2020, a spike of 856 reactions, were associated with coverage of governance failures. The overall pattern showed fewer but more sustained spikes for "Angry" reactions.

"Haha" Reactions: Selective Intellectual Humor

The "Haha" reactions on The Hindu reveal a pattern of humor and selective intellectuality, but it was only thirty-two unusual days. It is also the lowest among all reactions and outlets. When humor spiked, it was primarily on absurd situations. The main examples include: on September 10, 2020, the report on an attempt to "sell" the Statue of Unity, which got 2,551 reactions; on January 16, 2021, coverage of self-contradictory bureaucratic circulars got 2,028 reactions; on July 15, 2021, a piece on political promises impossible to fulfill received 1,890 reactions; and on August 17, 2020, a story highlighting tone-deaf statements by officials got 1,706 reactions.

"Love" Reactions: Appreciation for Quality Journalism

The Hindu's Facebook page reflected only thirty unusual days for the lowest count for the "Love" reactions, but it is the most meaningful engagement pattern. For example, a notable spike occurred on May 11, 2020, with 1,548 reactions. These reactions responded to the comprehensive series on healthcare workers, indicating a strong emotional resonance with the positive coverage. Other key examples included May 27, 2020, which received 1,318 reactions for content documenting environmental recovery, and June 28, 2020, which got 822 reactions related to community resilience stories.

"Sad" Reactions: Deep Empathy for Documented Suffering

The "Sad" reaction on The Hindu Facebook post engagement pattern reveals a deep sense of empathy during the COVID-19 pandemic, where one of the most striking examples occurred on May 17, 2020, when a post about Rampukar Pandit, a migrant worker who was unable to see his dying son, received 3,217 "Sad" reactions. Another notable example was the children's education crisis coverage on June 17, 2020, which received 1,489 reactions; and on September 25, 2020, the post reflecting public concern over long-term COVID-19 impacts received 919 reactions. There were forty-nine unusual days for the "Sad" reactions for The Hindu news outlet.

"Wow" Reactions: Surprise at Revelatory Reporting

Only twenty-seven days were marked by notable spikes for "Wow" reactions in The Hindu outlets. This was the lowest count, which reflects the post and its editorial tendency rather than sensational reporting. For example, on June 8, 2020, the outlet received 236 "Wow" reactions on the post for the release of exclusive data on COVID-19 recovery rates. In a similar instance, on June 28, 2020, the post received 181 reactions for the coverage of significant environmental transformations. Another notable story covered by The Hindu received 145 reactions for the reporting related to medical breakthrough reports.

The Times of India: Mass Reach and Extreme Responses

"Angry" Reactions: Channeling Mass Frustration

The Times of India (TOI) recorded the single highest spike in the entire dataset of about 14,806 "Anger" reactions on March 25, 2020, for the post related to coverage of youth attacking police during early lockdown enforcement, which reflects the profound public backlash. It was the second day of the nationwide lockdown. In total, TOI recorded forty-one unusual days for "Angry" reactions. In more depth, the temporal pattern of TOI's "Angry" reactions reveals important insights, such as extreme spikes during the early pandemic months (March–April 2020), and the obvious reason behind it was struggling with abrupt restrictions; more widespread anger across governance-related failures during the mid-pandemic period (May 2020–2021); and a few more targeted spikes seen in the later phase (2022), often tied to specific scandals. Some of the most important and dramatic percentage increases in "Angry" reactions include a 3,418% surge on June 25, 2020, which is linked to political hypocrisy exposés; another instance related to about a 4,238% increase on May 30, 2021, after reports of vaccine shortages; and similarly, a surge of 5,480% on January 16, 2021, on the post about investigations into the oxygen crisis.

"Haha" Reactions: Popular Irony and Mass Humor

The "Haha" reactions on Times of India's (TOI) Facebook page received fifty-eight unusual days, illustrating the usage of humor as a popular mode of engagement during the pandemic's often surreal and contradictory circumstances. Interestingly, a spike on April 14, 2020, which received 10,664 reactions, remains one of the highest "Haha" counts, responding to announcements of a lockdown extension delivered with unrealistically optimistic terms. Another notable instance occurred on October 22, 2020, with a surge of 7,006 reactions regarding the BJP's election promises of free vaccines in Bihar, which was a clear signal of the audience's sharp recognition of political opportunism. Another example of extreme percentage increases in "Haha" reactions is a staggering 127,566% rise on November 8, 2020, which was linked to political satire. A 20,000% increase was seen on August 13, 2021, for a post associated with bureaucratic absurdities. Another surge was observed with a 22,850% jump on February 25, 2022, following claims about the return to "normalcy" in the post-pandemic period.

Therefore, these patterns collectively demonstrate humor as both a coping mechanism and a form of social commentary during the COVID-19 crisis.

"Love" Reactions: Mass Appreciation for Hope

There were fifty-eight unusual days for "Love" reactions with bimodal distribution for Times of India's Facebook posts during the pandemic, reflecting either substantial spikes driven by universally beloved content or dramatic percentage increases in response to niche positive stories. For example, on July 8, 2020, a surge of 4,526 reactions celebrated healthcare workers, while later spikes showed more selective appreciation such as posts about vaccine success stories that received 1,254 reactions on March 1, 2021. Similarly, on April 24, 2021, and May 3, 2021, they received 991 reactions for recovery milestones and the return of public events. There were observed extreme percentage increases i.e. February 25, 2022: 16,266%; January 3, 2022: 12,100% for exceptional positive news stories that broke through audience fatigue and elicited significant engagement.

"Sad" Reactions: Collective Grief at Scale

The Times of India (TOI) had fifty-two unusual days for "Sad" reactions which tracked collective grief during the COVID-19 pandemic. Across these unusual days, these reactions closely mirrored the trajectory of India's COVID-19 related death tolls. On March 25, 2020, a count of 5,930 reactions, though it was not unusual due to the high baseline of engagement, the volume itself represented one of the highest absolute "Sad" counts and public recognition of the unfolding crisis. The temporal pattern emerges as the first wave for shock and sudden grief with high absolute numbers; second wave for sustained sorrow with consistent elevated responses; and endemic phase for selective sadness with high percentage increases and lower absolutes. Notable surges include 2,933 "Sad" reactions with milestone death counts on December 7, 2020. Another post related to the peak of the migrant crisis had 4,131 "Sad" reactions on May 27, 2020. Similarly, the stories reported about the healthcare system's collapse on July 6, 2020 received 2,449 "Sad" reactions. These reaction patterns give traces of public mourning and emotional engagement during the crisis time for key pandemic events.

"Wow" Reactions: Mass Surprise and Wonder

The Times of India, with sixty unusual days, had the highest among all other news outlets, as demonstrated through the use of "Wow" reactions. In the beginning, the spike in these reactions was closely associated with public astonishment and surprise regarding virus news, such as on April 12, 2020, with 984 reactions related to rapid spread documentation. Similarly, on May 19, 2020, there were 820 reactions for the post about unexpected symptom reports, and the report on global comparison statistics received 686 reactions on April 23, 2020. With the progression of the pandemic, the nature of astonishment and surprise became more selective and nuanced, reflecting a substantial increase in "Wow" reactions, such as on November 8, 2020, with a 4,800% increase for the post about vaccine development speed. A 2,700% rise was also observed on February 3, 2021, following reports of new mutations, and a 2,100% increase on December 26, 2021, linked to emerging information about the Omicron variant.

There are viral posts that serve multiple analytical purposes in understanding public engagement during the COVID-19 pandemic, from news outlets that illustrated public engagement during the COVID-19 pandemic in India making "Facebook reactions" an important indicator of emotional responses, especially during crisis situations (Full documentation with URLs and screenshots is provided in Appendix E.).

These posts validate the time series analysis by providing concrete examples of content that drove unusual spikes in engagement, while demonstrating how Facebook users employed different types of "Facebook Reactions" to express their emotions about various aspects of the pandemic.

The posts illustrate how different media outlets' news coverage generated distinct patterns of emotional responses, such as philanthropic stories receiving predominantly "Love" reactions while lockdown enforcement news triggered mostly "Angry" reactions. Moreover, these examples ground how the twenty-five thematic clusters were expressed in real news stories, connecting the abstract computational findings to actual Facebook media content.

These posts are valuable because they: represent peak moments of public emotional engagement, show how different types of pandemic-related news triggered emotional responses, and demonstrate variations in coverage and audience reactions across different media outlets. Moreover, they provide concrete examples of sentiment patterns manifested in actual content. Each post captures a different aspect of the pandemic narrative and public discourse, making "Facebook reactions" an important indicator of emotional responses, especially during crisis situations.

Below are the key viral posts from news outlets that illustrated public engagement during the COVID-19 pandemic in India:

Hindustan Times:

For "Angry" reaction - The post about a UK national alleging that Mumbai airport's COVID test and quarantine protocol was a "scam" generated 1,707 "Angry" reactions on January 4, 2022. This reflects public frustration with perceived mismanagement.

For "Haha" reactions - The post on July 27, 2020, about Prime Minister Modi claiming India was in a "much better situation" in fighting COVID-19 generated 4,311 "Haha" reactions, suggesting the public found the claim ironic given India's ongoing challenges.

For "Love" reactions - On August 28, 2020, a post about actor Sonu Sood pledging to help students travel to exams during the pandemic received 6,244 "Love" reactions, showing appreciation for this philanthropic act.

For "Sad" reactions - A post on March 29, 2020, about a German finance minister's suicide, allegedly due to COVID-19 economic stress, garnered 1,527 "Sad" reactions as the public empathized with this tragic consequence of the pandemic.

For "Wow" reactions – On March 26, 2020, a post about pop culture works that seemingly "predicted" the coronavirus pandemic, including a 1981 novel mentioning a "Wuhan-400" virus, received 1,045 "Wow" reactions as people marveled at these coincidences.

Indian Express:

For "Angry" reactions - A post on July 13, 2020, about people violating curfew and traveling without masks generated 1,465 "Angry" reactions, reflecting disapproval of non-compliance with health guidelines.

For "Haha" reactions - On January 2, 2021, a post about Prime Minister Modi urging documentation of COVID-19 efforts received 3,410 "Haha" reactions, possibly perceiving the request as ironic or ill-timed.

For "Love" reactions - A post on October 16, 2020, about a migrant mother and her children being depicted as goddess idols generated 2,227 "Love" reactions, showing compassion for migrants' plight.

For "Sad" reactions - A post on March 28, 2020, about the exodus of migrant workers from Delhi generated significant "Sad" reactions, reflecting public empathy for their difficult circumstances.

For "Wow" reactions - An April 3, 2020, post showing the Dhauladhar mountain range becoming visible from Jalandhar due to reduced pollution during lockdown received 519 "Wow" reactions, as people marveled at this unexpected environmental impact.

The Hindu:

For "Angry" reactions - On April 2, 2020, a post about devotees defying lockdown orders to gather at temples received 1,077 "Angry" reactions, showing frustration with religious gatherings undermining containment efforts.

For "Haha" reactions - A post on April 6, 2020, about a prank attempt to "sell" the Statue of Unity to fund COVID-19 efforts generated 2,913 "Haha" reactions, with the public finding humor in the absurd listing.

For "Love" reactions - On March 28, 2020, a post about actor Akshay Kumar donating ₹25 crore to the PM's relief fund received 2,216 "Love" reactions, appreciating this charitable contribution.
For "Sad" reactions - A May 17, 2020, post about Rampukar Pandit, a migrant worker whose photo weeping by a Delhi Road became symbolic of the migrant tragedy, generated 3,021 "Sad" reactions as people sympathized with this heartbreaking story.

For "Wow" reactions - A March 28, 2020, post about Akshay Kumar's ₹25 crore donation to the PM's relief fund received 190 "Wow" reactions, indicating amazement at the size of the contribution.

The Times of India:
For "Angry" reactions - On March 25, 2020, a post about youth clashing with police trying to enforce lockdown in Ernakulam received 4,833 "Angry" reactions, with the public disapproving of the violent disobedience.

For "Haha" reactions - A post on October 22, 2020, about BJP promising free COVID-19 vaccines in their Bihar election manifesto generated 5,624 "Haha" reactions, possibly finding the overt political motive humorous or absurd.

For "Love" reactions - On July 8, 2020, a post related to social issues during the pandemic received 4,259 "Love" reactions, demonstrating public solidarity.

For "Sad" reactions - A March 26, 2020, post about laborers and migrant workers facing hardships during lockdown garnered 4,583 "Sad" reactions, showing empathy for their struggles.

For "Wow" reactions - An April 12, 2020, post about the Ganga waters becoming clean enough for ritual sipping (achaman) in Haridwar due to reduced pollution received 682 "Wow" reactions, as people were amazed by this environmental change.

The above viral posts from the four major Indian news outlets i.e. Hindustan Times, Indian Express, The Hindu, and The Times of India offered genuine insight into public discourse and their sentiment and engagement during the certain period of the COVID-19 pandemic. Here we validate the findings from the time series analysis with the illustration of nuanced usage of the “Facebook reactions” and the connection of the thematic clusters, liked as the sentiment scores to triggering topics and the highlighting the engagement across outlets.
The time series analysis validation identifies a specific period where "Facebook reactions" exhibit unusual spikes and anomalous patterns. The viral posts from this timeframe provide concrete examples of content that drove high engagement, correlating with the exact data points where real-world events occurred.

For example, a Hindustan Times post on January 4, 2022, which reported on a UK national's allegation that Mumbai airport's COVID-19 testing and quarantine protocol was a "scam," generated a staggering 1,707 "Angry" reactions. This significant number of "Angry" reactions reflected public frustration and disapproval of the perceived mismanagement and corruption during a critical phase of the pandemic.

Similar to that story, the Indian Express post on July 13, 2020, which reported violations of curfew orders and maskless travel, showed a sudden surge in "Angry" reactions in the time series. The post's 1,465 "Angry" reactions underscored the public's exasperation with actions undermining collective efforts to control the virus's spread.

These real-world examples validate the time series findings and confirm that the identified spikes in emotional reactions were not merely statistical anomalies but were triggered by specific resonant events in the unfolding pandemic narrative.

The viral posts demonstrate how Facebook users strategically employed different reaction options to express their emotions regarding various aspects of the pandemic experience. The public response to news content was not homogeneous but rather varied based on the nature of the content, revealing a spectrum of sentiments.

Posts related to philanthropic efforts and community solidarity tended to receive higher volumes of "Love" reactions. The Hindustan Times post on August 28, 2020, reporting actor Sonu Sood's pledge to help students travel to examination centers during the pandemic, garnered 6,244 "Love" reactions. Similarly, The Hindu's post on March 28, 2020, about actor Akshay Kumar's donation to the Prime Minister's relief fund received 2,216 "Love" reactions. These examples demonstrate public appreciation and admiration for individuals who supported others during the critical period of the pandemic.

On the contrary, posts that highlight the irony or absurdity of a certain situation often get "Haha" reactions. For example, The Hindustan Times post on July 27, 2020, which reported on Prime Minister Modi's claim that India was in a "much better situation" in fighting COVID-19 during the period, received 4,311 "Haha" reactions. This suggests many users found that the claim was out of touch or incongruous with the reality of India's ongoing challenges during the pandemic period.

The posts that were related to heart-breaking news frequently evoked "Sad" reactions as users empathized with the profound human cost of the COVID-19 pandemic. The Hindu's post on May 17, 2020, narrating the story of a migrant laborer who was unable to see his dying son due to lockdown restrictions, generated 3,021 "Sad" reactions. Similarly, The Times of India's post on March 26, 2020, which brought the story of migrant workers and their plight of bearing

the brunt of the lockdown, received 4,583 "Sad" reactions. These posts struck a chord with users and evoked collective sorrow and compassion for the most vulnerable sections of society.

On the other hand, reports of lockdown violations, conflict, and mismanagement tended to trigger more "Angry" reactions. The Hindu's post on April 2, 2020, about devotees defying lockdown orders and gathering in the temple, received 1,077 "Angry" reactions, reflecting the public's disapproval of this religious gathering that undermined containment efforts. Likewise, The Times of India's post on March 25, 2020, about a youth who clashed with police while defying the lockdown enforcement, saw a surge of 4,833 "Angry" reactions, with users condemning the violent disobedience that risked spreading the virus further.

These examples illustrated the multidimensionality of public sentiment during the pandemic; anger over non-compliance and mismanagement co-existed with love for philanthropy and solidarity, while sorrow about personal tragedies mingled with humor about the absurdities of the situation. By employing different "Facebook reactions," users actively participated in the emotional narrative of the pandemic, using Facebook's affordances to convey their emotional responses to the crisis.

If we consider the viral posts and their corresponding Sentiment Scores to triggering topics, it also provides a qualitative lens to complement the quantitative sentiment analysis. This allows us to connect the sentiment score to the specific context and their topics.

With the example of the posts, where the negative sentiment scores often involved issues of rule violations, government autocracy, and heartbreaking human loss, The Times of India's post on March 25, 2020, about youth clashing with police during lockdown enforcement, and The Hindu's post on May 17, 2020, about a migrant worker's tragic loss both gathered high volumes of "Angry" and "Sad" reactions respectively, contributing to the negative sentiment score.

On the other hand, the posts related to positive sentiment frequently featured themes of philanthropy, community solidarity, or resilience. In The Hindu, the post on March 28, 2020, about Akshay Kumar's donation to relief funds, and the Indian Express post on October 16, 2020, depicting a migrant mother as a goddess, both received and attracted a higher number of "Love" reactions and boosted the positive sentiment as well.

If we consider viral posts by connecting thematic clusters to real-world content, the topic modeling analysis identified 25 key conversation clusters that encapsulate the main pandemic discourses. These viral posts serve as the real-world embodiment of these abstract thematic clusters, making the findings more tangible and interpretable

Correlation within news outlets

If we observe the general prospective of the correlations for all news outlets, we find that the outlets “love and “Wow” consistently got the strongest correlation. The Times of India got the highest overall correlations in all Facebook reactions. Whereas “Haha” is placed weakest correlation with other Facebook reactions across all news outlets. “Angry” and “Sad” have moderate correlations across the media outlets. While Indian Express got the weakest correlations overall and The Times of India had the strongest one. Please refer to correlation plots in Appendix B, Tables 2-5.

1. Correlation Hindustan Times-

   Here, is the correlation among the five Facebook reactions (Love, Haha, Wow, Angry, and Sad). The strongest correlation is between “Wow” and “Love” i.e. 0.67; Whereas “Angry” and “Sad” have a relatively strong correlation i.e. 0.64 and “Haha” got the weakest correlations with other emotions overall.
2. Correlation Indian Express-

   The strongest correlation is between “Wow “and “Love” i.e. 0.78 and “Haha” get much weaker correlations with other reactions. However, “Angry” and “Sad” got a moderate correlation of 0.56

3. Correlation The Hindu-

   Here, we got a very strong correlation between “Wow” and “Love” which is 0.84; Whereas “Wow” got a relatively strong correlation with all other Facebook reactions. Reaction “Haha” got the weakest correlation with other Facebook reactions, particularly with Sad i.e. 0.38

4. Correlation The Times of India-

   Here we got an extremely strong correlation between “Wow” and “Love” reactions which is 0.88. We could observe overall correlation is much higher, even the weakest correlation i.e. “Haha” with “Sad” at 0.56 is stronger than other news outlets.

Correlation Across Outlets

Here is the relationship between Facebook reactions across the four new outlets: Hindustan Times, Indian Express, The Hindu, and The Times of India. There are all Correlations are positive and strong above 0.6 which indicates that Facebook reactions/emotions tend to be similar across the new outlets. Please refer to Table- Correlation across outlets.

We can observe the Strongest correlation between The Times of India and The Hindu (0.80); the second strongest for The Times of India and Indian Express (0.77); The Times of India and Hindustan Times (0.75); Fourth strongest is between The Hindu and Indian Express (0.69); and the Fifth strongest is The Hindu and Hindustan Times (0.68); whereas the Weakest correlation is Indian Express and Hindustan Times (0.61)

The Times of India got the strongest correlations with all other outlets, suggesting its emotional/ Facebook reaction patterns are most representative of the overall trend. The Hindu shows a strong correlation with all outlets, especially together with The Times of India.

Also, Indian Express got a strong correlation with The Times of India but the weakest for Hindustan Times. Most interesting Hindustan Times expresses the most variation in its correlations with other news outlets. Overall, we can say it has the strongest correlation with The Times of India, and weakest with Indian Express.

** The Times of India appears to be the "central" or representative news outlet in terms of Facebook reactions.

5.2 Topic Modeling and Cluster Analysis

After the analysis of Embedding-based topic modeling, we got the file which contained information about twenty-five clusters with their appropriate labeling. Each cluster is attributed by several headings with characters. The major finding of those clusters is twenty-five in number, with their names (labels), numerosity (number of items in that cluster), whiteness (Unclear/without any context), centroid (filled in the center), and label coverage (label covered in number). Please refer the Table 1 for labeled clusters for better understanding.

5.2.1 Identified COVID-19 News Topics and Clusters

In the context of their labels, we found all are related to India with a wide range of COVID-19 topics, such as COVID-19 Research and Technological Innovations, COVID-19 Response and Impact Analysis in India, Indian Political Leadership's Response to COVID-19. And Celebrity Responses and Public Engagement During the COVID-19 Pandemic and so on. The cluster covered and summarized a large amount of COVID-19-related information or news with particular emphasis on the Indian geographic area and the responses and measures against the pandemic.

Cluster	Numerosity	Whiteness	Centroid	Label	Label Coverage
1	81	2993.99		Indian Railways' COVID-19 Response and Adaptations	1
2	430	129891.48		Adaptations and Innovations in Daily Life and Services During COVID-19 Lockdown	0.2
3	247	36282.16		Philanthropic Responses to COVID-19 Pandemic	0.31
4	359	87429.43		Global Political and Health Responses to COVID-19 Pandemic	0.24
5	550	207987.27		COVID-19 Research and Technological Innovations	0.16
6	282	50523.1		Sports Community Response to COVID-19 Pandemic	0.29
7	341	82654.01		COVID-19 Impact and Response Measures Across Various Sectors and Countries	0.23
8	464	134874.61		Impact of COVID-19 Lockdown on Agricultural and Migrant Communities	0.17
9	277	52952.65		Recovery and Impact of COVID-19 on Public Figures and Global Communities	0.32
10	301	53203.93		COVID-19 Response and Impact Analysis in India	0.31
11	360	84271.57		Celebrity Responses and Public Engagement During the COVID-19 Pandemic	0.23
12	241	30498.29		Global Impact and Responses to COVID-19 Pandemic	0.33
13	98	4558.51		Global Debate and Diplomacy Over Hydroxychloroquine Use and Export During COVID-19 Pandemic	0.78
14	180	22561.64		Impact of COVID-19 on Global Sports Events and Athletes	0.45
15	333	71782.9		Global Economic Impact and Response Measures During the COVID-19 Pandemic	0.24
16	346	63691.55		Indian Political Leadership's Response to COVID-19	0.23
17	244	37358.58		Community and Government Initiatives for COVID-19 Prevention and Protection	0.34
18	219	27279.46		Challenges and Strategies in COVID-19 Testing and Healthcare Response in India	0.37
19	502	152205.79		COVID-19 Containment and Response Efforts in India	0.17
20	336	72809.74		Community and Frontline Support During COVID-19 Crisis	0.21
21	233	27178.19		COVID-19 Spread and Controversy Linked to Tablighi Jamaat Gatherings	0.31
22	341	57160.43		Extended National Lockdown and Government Responses to COVID-19 in India	0.24
23	435	81214.01		COVID-19 Crisis Management and Lockdown Measures in India	0.18
24	458	137472.86		Enforcement and Impact of COVID-19 Lockdown Measures by Police and Authorities	0.17
25	438	115152.76		COVID-19 Impact and Response in India	0.18

Table 3 - *Labeled clusters*

5.2.2 Cluster Sizes, Label Coverage, and Cohesiveness

If we look into the Cluster sizes, the numerosity varies widely low as Cluster 1 for 81 and to high cluster 5 for 550. Whereas the label coverage shows from 0.17 (17%) to 1 (100%) significantly. The high coverage of about 0.78 (78%) for Cluster 13, which is related to "Global Debate and Diplomacy Over Hydroxychloroquine Use and Export During COVID-19 Pandemic". The label coverage value range is 0 to 1, which proves how the label covered the topic assigned to it well in the cluster, Lower values like 0.16 for Cluster 5, show the label partially covered the cluster or less cohesive content. In cluster 1, we can

see the label coverage is also 1, which shows how it is assigned the label very well. Mostly all topics cover the Indian arena concerning COVID-19, despite a few labels covering Global issues and the responses to the COVID-19 pandemic. After getting the analysis with a result of 25 labeled clusters, we conducted sentiment analysis for each cluster across the clusters.

We find a wide range of sentiment scores from -0.18 to 0.07, which are negative and positive as well as the user reactions came out widely from -126.49 to 129.32. Whereas the number of stories counts per cluster ranges from 80 to 495. Please look into Appendix D, Figure 2 for articles by cluster.

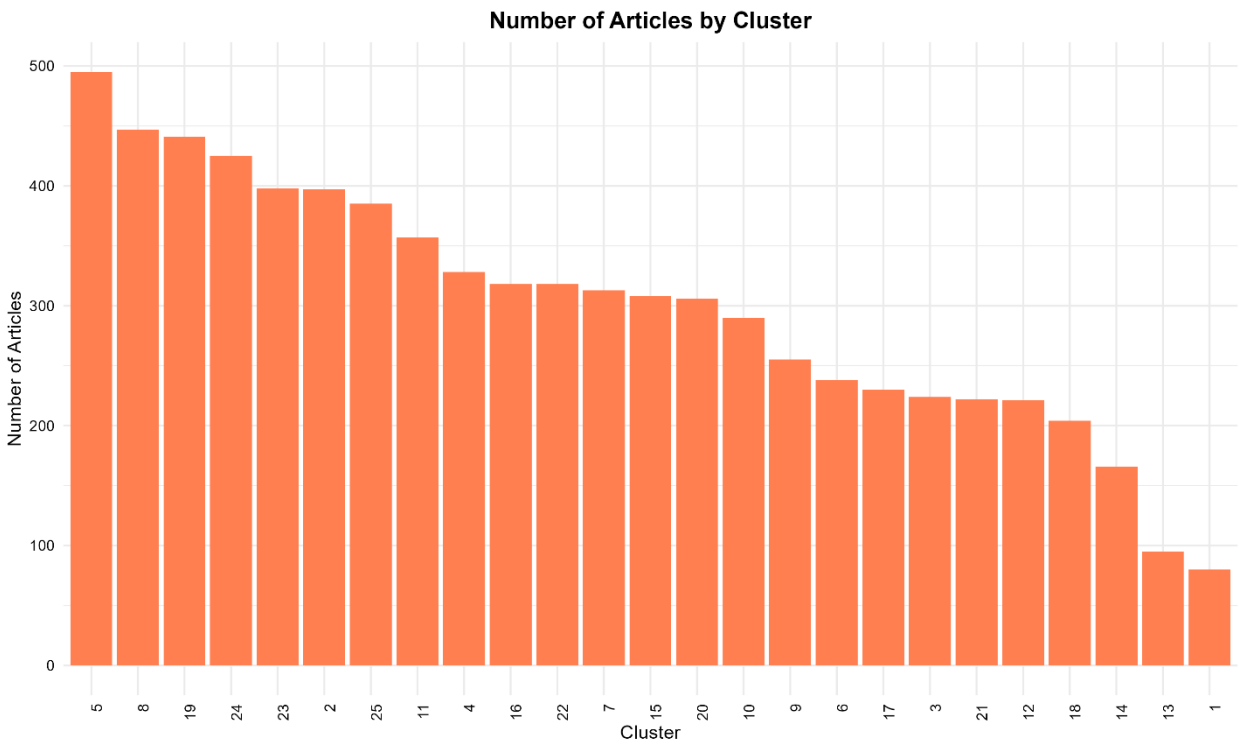

Figure 10 - *Articles by cluster*

5.3 Sentiment Analysis and User Engagement

We analyzed the sentiment variation and users' reactions across different clusters and news outlets, revealing significant differences in COVID-19 related

content. The sentiment scores varied widely alongside users' reactions. These variations demonstrated distinct patterns in how different news outlets conveyed pandemic information and how audiences responded through "Facebook reactions".

Here, we can observe the sentiment variation, while user reaction is always not correlated with sentiment. The number of stories per cluster varies based on user engagement, like largest cluster is 5 (COVID-19 Research and Technological Innovations) with a count of stories 495 with moderate user reactions of 16.86, and the smaller one is cluster 13 (Global Debate and Diplomacy Over Hydroxychloroquine Use and Export During COVID-19 Pandemic) with the story count is 95 with the high user reaction 56.92

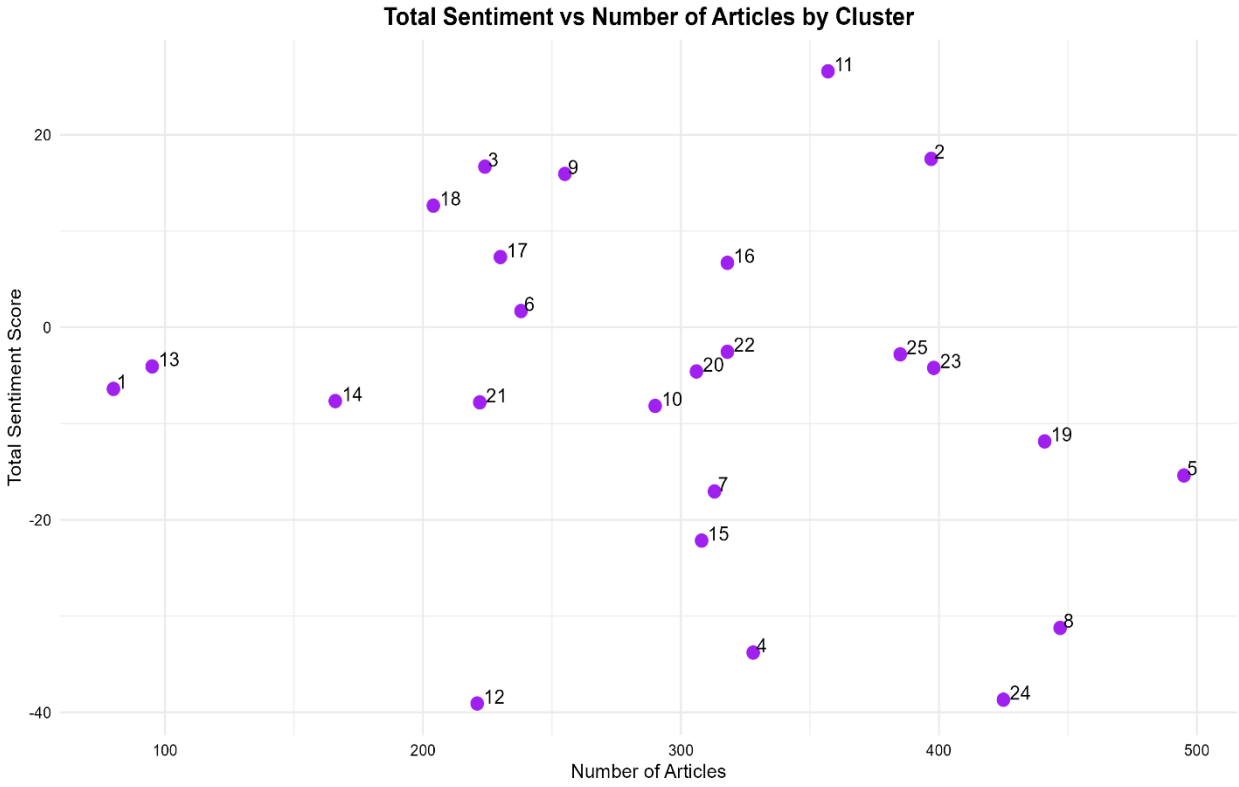

Figure 11 - *Sentiment vs articles scatter*

If we take the research questions 1 and 2 related to the main topics and differences in sentiment scores that varied from positive to negative, they are likely to reflect their differences in the content/topics discussed within each

cluster. Better to say why specific clusters have positive or negative sentiment scores.

Here we need to go into the depth of their content by a) Examining the content of articles/stories within each cluster; b) Identifying the common themes/topics in each cluster; c) Considering the time frame of the articles/stories in each cluster.

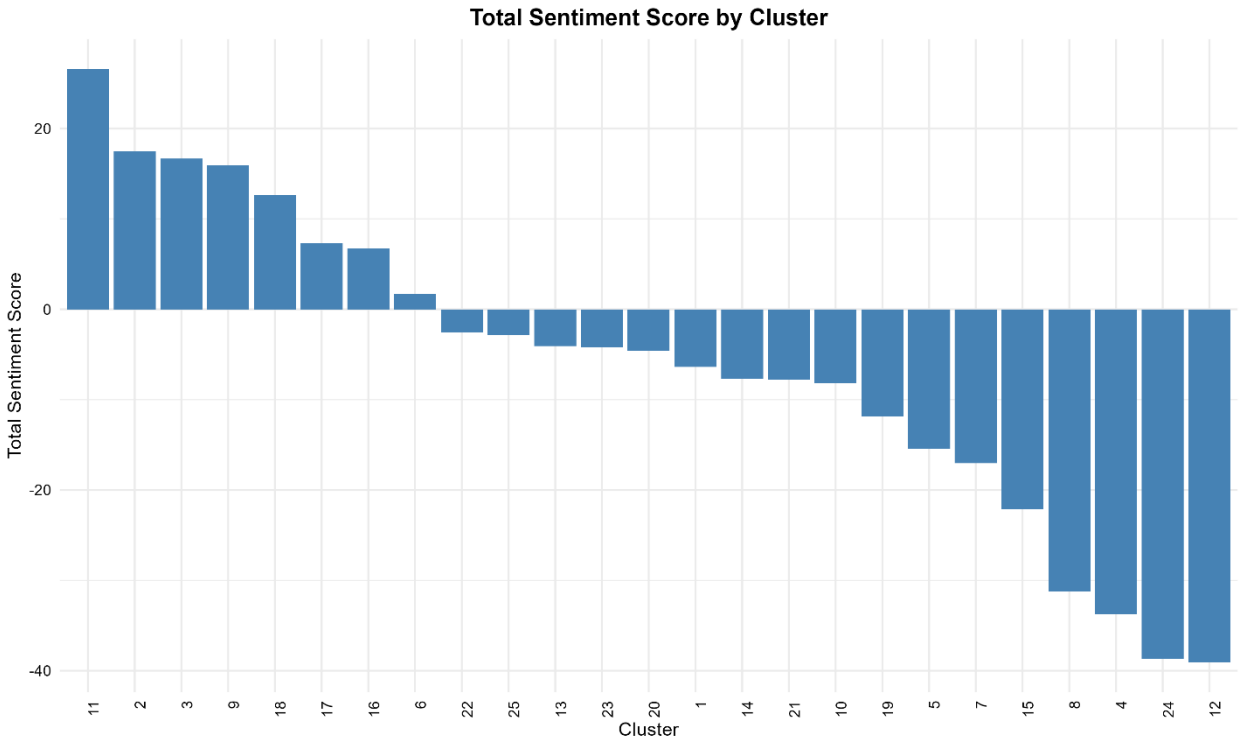

Figure 12 - *Total sentiment by cluster*

5.3.1 Sentiment Scores and User Reactions across Clusters

Here a few notable clusters, sentiment scores, and their corresponding labels with their examples are discussed: Cluster 2 has a positive sentiment, and it has the label "Adaptations and Innovations in Daily Life and Services During COVID-19 Lockdown"- (avg_sentiment: 0.04), this positive sentiment likely reflects the stories about people and businesses finding creative solutions to challenges, which tends to be viewed as positively. Example- “From BSNL to Apple and Reliance Jio, here is a list of all the freebies that you can enjoy during the lockdown”.

For cluster 3 "Philanthropic Responses to COVID-19 Pandemic" - (avg_sentiment: 0.074), the News related to charitable actions, charity events, donations, and community support initiatives typically generate sentiment positively. Example- “Contributing their bit to support Prime Minister Narendra Modi in the fight against coronavirus, a 6-year-old and a 5-year-old donated their piggy bank to the PM- CARES fund..... their mother, Rita.”

For cluster 11 "Celebrity Responses and Public Engagement During the COVID-19 Pandemic" (avg_sentiment: 0.07), Celebrities' involvement in social causes often receives positive coverage. Example- “Doctor-turned-actor Ashish Gokhale is on 24x7 duty at a private hospital treating the coronavirus patients.” Now if we talk about the negative sentiment then we have to look into Cluster 4 "Global Political and Health Responses to COVID-19 Pandemic" (avg_sentiment -0.10), the negative sentiment reflects the criticism of government responses or the severity of the health crisis. For example, “Chinese authorities responded to allegations of discrimination. People of African descent were allegedly facing discrimination in Guangzhou and were forcibly evicted and denied entry by hotels in the city.”

For cluster 12 "Global Impact and Responses to COVID-19 Pandemic" (avg_sentiment -0.18), here in this cluster news holds the widespread negative effects of the pandemic. Example- “Italy and Spain, the two hardest-hit European nations, expressed hope that the crisis was peaking in their countries, though Italian officials said the emergency is far from over as infections have plateaued but not started to decline.....”.

In cluster 24 "Enforcement and Impact of COVID-19 Lockdown Measures by Police and Authorities" (avg_sentiment -0.09), the stories about strict enforcement measures and their impact on people's lives often generate negative sentiment. For example- “The home ministry has directed all states and union territories to ensure strict compliance of lockdown measures to fight COVID-19 and not allow any social, religious gathering or procession.”

5.3.2 Relationship between News Sentiment and User Engagement

If we consider the sentiment vs. users' reaction, the result reveals significant differences in how these news outlets are perceived and engaged by their audience. Please refer to Fig overall sentiment vs user reaction for more.

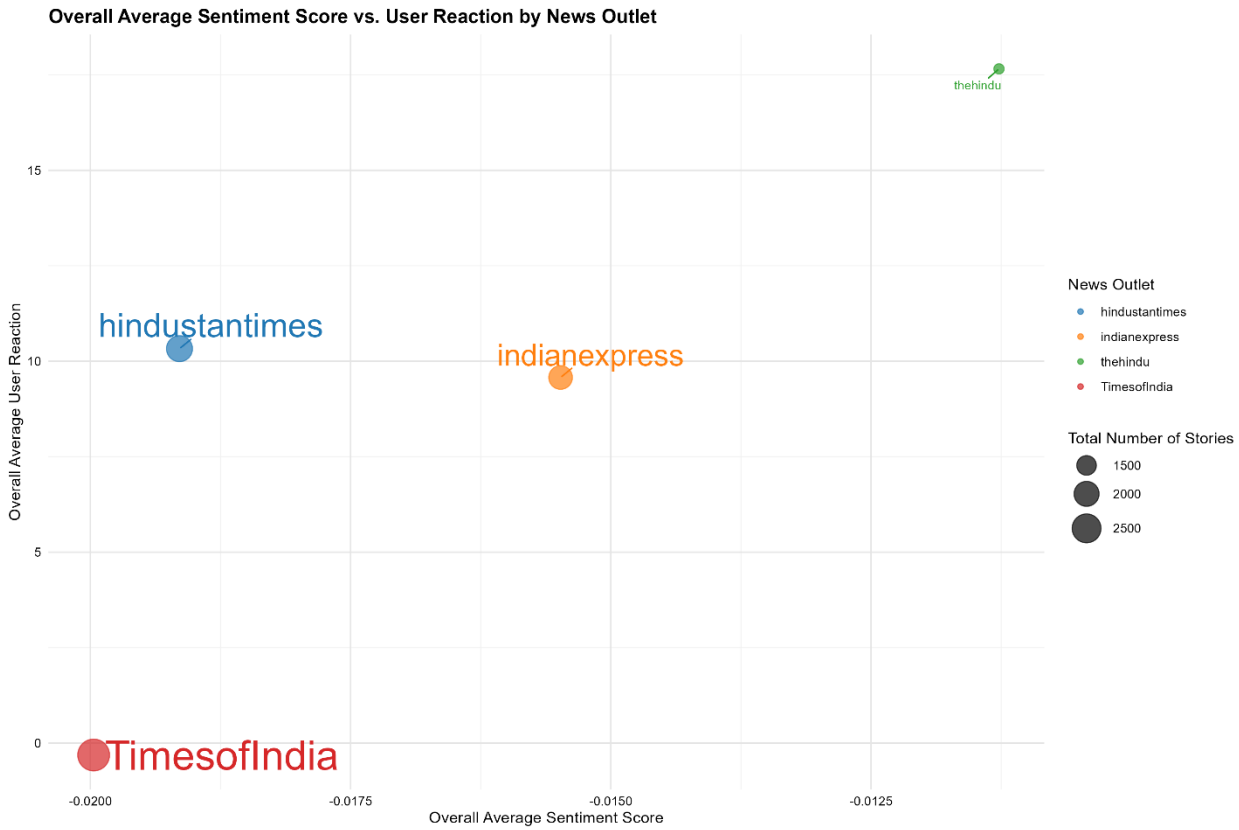

Figure 13 - *Overall sentiment vs user reaction*

This relationship shows Sentiment Score and User Reaction for different news outlets. All outlets have negative average sentiment scores from about -0.02 to -0.01, where the Times of India has the most negative while The Hindu gets the least negative. Here User reaction is very widely observed from near to Zero for the Times of India and for The Hindu, it is 17.5 whereas Hindustan Times and Indian Express fall in the middle range for user reactions. If we look into individual outlets, we have found the highest user reaction and least negative sentiment for The Hindu, which suggests that received most positively by users. For Times of India, the lowest user reaction and most negative sentiment means its content gets more controversial or negatively perceived. The second-highest

user reaction with a sentiment score in the middle range is of Hindustan Times. Indian Express gets third in user reactions with a sentiment score slightly more negative than Hindustan Times. Here a positive correlation is found between sentiment score and the user reaction, as sentiment became less negative, and users' reaction tended to be more positive. Hindustan Times has more stories while The Hindu has a few stories. It stands out with the higher users' reactions compared to its sentiment score which suggests the factors beyond sentiment influence the user's engagement. Times of India has an outlier in the opposite direction with low users' reactions, despite of sentiment score close to others.

Overall, these results reveal the significant differences between what these news outlets receive and user engagement, which could be based on several factors of target audience, writing style, social media strategy, target audience or content type, etc.

The distribution of average sentiment scores across the different clusters for four major Indian news outlets tends to have slightly negative to neutral sentiment. The news outlet Hindu gets the most positive leaning with the highest variability. Whereas the Times of India shows more consistently negative sentiment, the Hindustan Times and Indian Express fall in between them. This variation across the clusters points out the subject matter influences the sentiment coverage for all four new outlets. This (Figure 14 - sentiment distribution by outlet) visualizes clear sentiment distribution.

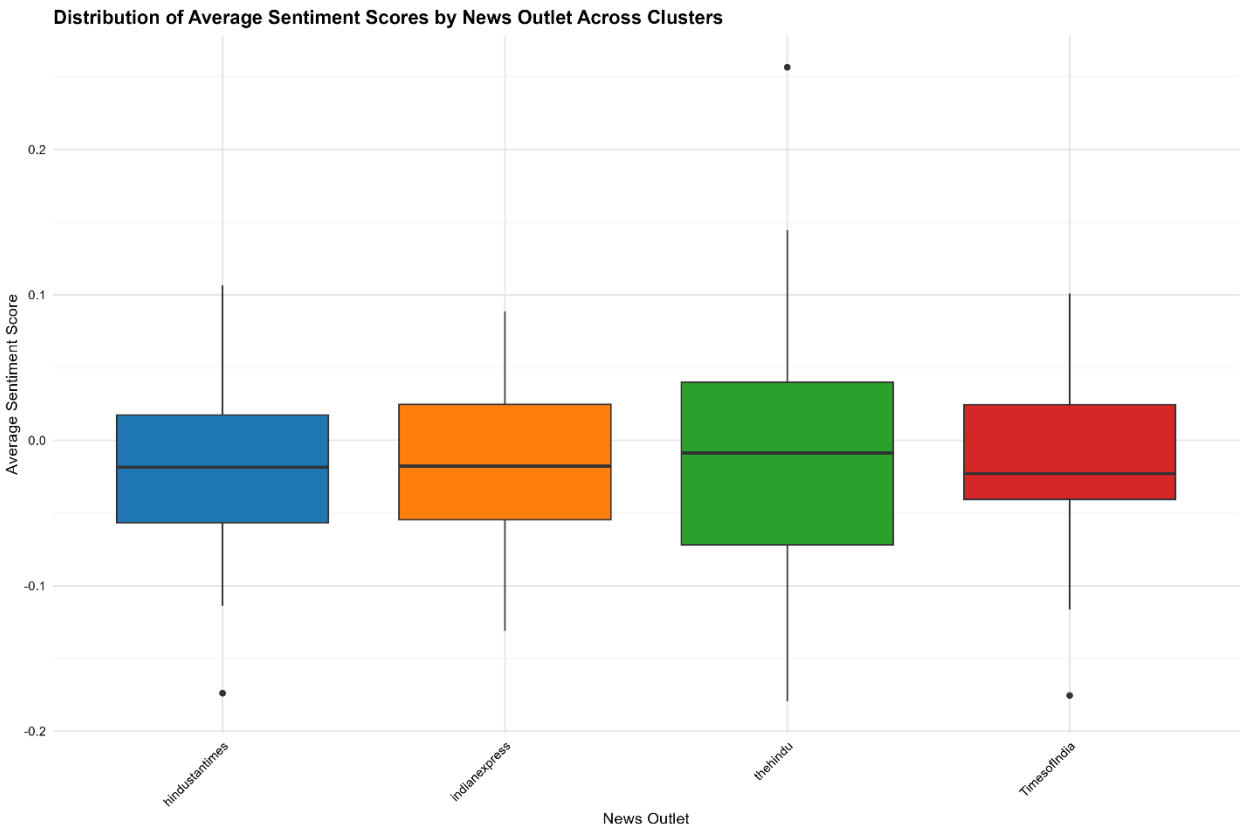

Figure 14 - *Sentiment distribution by outlet*

Here overall sentiment scores for all outlets fall between -0.2 and 0.25 with most data concentrated between -0.1 and 0.1 which suggests the news outlets tend to be slightly negative to neutral with some variants going to positivity.
All these outlets have median sentiment scores slightly below zero which is the indicator of the tendency toward slight negativity. The Hindu appears highest, then Indian Express followed by Hindustan Times, and Times of India has the lowest.

If we compare the outlets there are distinguished differences but the overall sentiment distribution of the four overlaps, where The Hindu has a slight edge in positive sentiment while Times of India tends to lean toward negative. And Hindustan Times and Indian Express occupy the middle ground with slightly more positive for Indian Express. Symmetrically the distribution for Hindustan Times and Indian Express shows symmetric around the median, while The Hindu is slightly positive, and Times of India shows a slightly negative skew.

5.3.3 Variations in Sentiment and Engagement across News Outlets

The presence of outliers and the range of boxes indicates that sentiment varies across the different news clusters/topics/themes, it is for the sentiment dependency on the subject matter being reported.

Moreover, there is another view to investigate the user reaction distribution by outlet, where all four news outlets tend to have negative to neutral sentiment. Here we find the subtle differences in their sentiment profiling. The Hindu shows the most positive leaning highest variability and the Times of India toward more consistent negative sentiment; the Hindustan Times and Indian Express fall in between them. Please refer to the Fig- User reaction distribution by outlet.

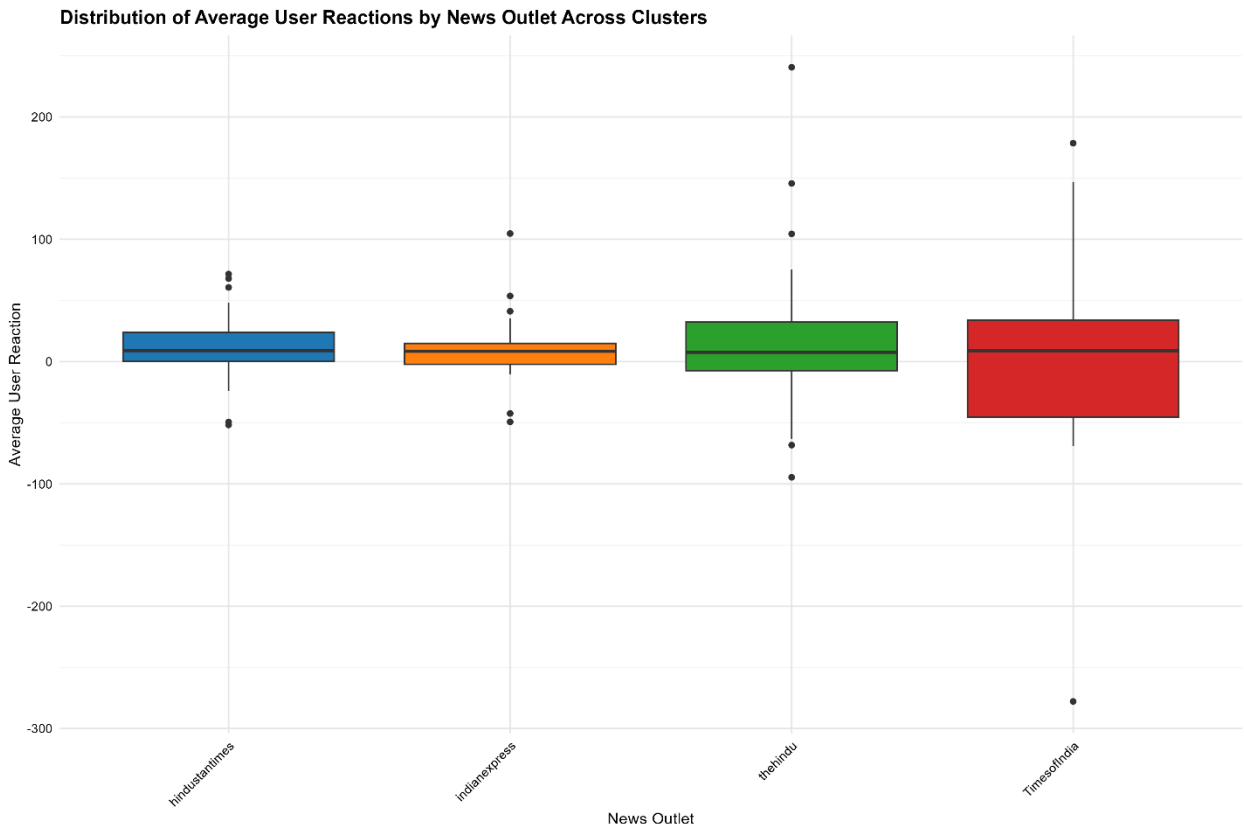

Figure 15 - *User reaction distribution by outlet.*

The sentiment scores show that all four outlets fall between -0.2 and 0.25, with most data concentrated between -0.1 and 0.1 which means these outlets tend to be slightly negative to neutral with some variation going to the territory of positivity.

All outlets have median sentiment scores slightly below zero indicating a tendency towards slightly negative sentiment, whereas The Hindu has the highest median followed by Indian Express then Hindustan Times and the lowest median score is for Times of India. Symmetrically the distribution for Hindustan Times and Indian Express is fairly around their median, and The Hindu has its distribution slightly skewed toward the positive while Times of India gets a slightly negative.

The comparison across the outlets shows The Hindu has a slight edge with positive sentiment while the Times of India has more negative. And Hindustan Times with Indian Express get the ground middle whereas Indian Express shows slightly positive sentiment. We found there is a moderate positive correlation of 0.37 between average User reaction vs. average Sentiment. Then, the analysis for the residual outliers and their clusters. Please refer to the Figure (Scatterplot Margin error).

Here is a comprehensive Outlier clusters analysis (see Appendix D, Table 4-Outlier cluster summary) that shows which clusters contain outliers and how many outliers are in each cluster. There are a few clusters, e.g. cluster 3 has the highest number of outliers (27) then Cluster 24 follows with 22 outliers followed by Clusters 20 and 21 both have 17 outliers each. And many clusters (1, 12, 13, 19) have only one outlier. Clusters with several outliers e.g., 3, 24, 20, 21 might stand for unique patterns or sub-groups within the overall trend. It can be considered the context of each cluster based on time and period; user demographics etc. to understand the deviations.

Chapter 6: Discussion

6.1 Interpretation of Results in the Context of Existing Literature

Our study provided a comprehensive analysis of the COVID-19-related news coverage by the major Indian news outlets and the corresponding public engagement on Facebook during the critical period of the pandemic.

First, we demonstrated through the time series analysis that we found a significant spike in user engagement during the early stages of the pandemic and then followed by a gradual decline over time. This finding is consistent with the previous studies that observed social media activities and information-seeking behavior during the initial phase of the crisis (Kleiner, 2024; Manningham et al., 2024; Ogbodo et al., 2020). This surge in user engagement can be attributed to people's need to be informed timely and accurately about the evolution of the crisis, including the collective sense of anxiety and uncertainty.

Second, the analysis shows the identification of several “unusual days” and sudden changes in “Facebook reactions” for the four news outlets. These rising spikes often coincide with an event or situation-based information such as the

announcement of public health safety, announcement of lockdowns, prominent public figures news, high-profile cases, or the progression of significant milestones of the pandemic. These findings highlight the role of key events that drive the users' engagement on social media and shaping the public discourse (Bünzli & Alizadeh-Afrouzi, 2024; Salgado & Bobba, 2019; Heiss et al., 2019). Third, with the topic modeling and the cluster analysis, we identified the wide range of themes and sentiments associated with COVID-19 news coverage. We identified twenty-five thematic clusters that are aligned with the existing literature done before, those highlighting the multifaceted impact of the COVID-19 pandemic, ranging from the Impact of the COVID-19 Lockdown, political responses, global impact, and personal stories to Government and public responses for social consequences (Lin & Luo, 2023; Prados-Peña et al., 2022; Pratama & Firmansyah, 2022).

Fourth, the sentiment analysis reveals varying emotional responses across clusters and news media outlets. Positive sentiment is associated with topics like philanthropic responses and adaptations to daily life, while negative sentiment correlates with topics related to global impact and lockdown enforcement measures, these findings resonate with the previous studies for the emotion and public reactions (Rothschild et al., 2024; Wang et al., 2024; Zhang et al., 2021). We observed the rage-baiting phenomenon during the COVID-19 period, examining Facebook reactions within the Indian digital news landscape. It revealed systematic exploitation that predominantly targeted crisis-related anxieties. The designed content generated measurable emotional responses and amplified engagement.

For example, the cluster related to anti-China sentiment demonstrates sophisticated narrative construction through progressively inflammatory content. The content evolved from factual reports to provocative interpretations of news events. With documented "Angry reactions," responses increased from 134 to 680 across similar posts. The post "Chinese Govt bars research on coronavirus origin" received 411 angry reactions, while "Here's how China misled the world on coronavirus" generated 680 angry reactions. This indicates

successful audience capture through repeated exposure and incrementally inflammatory content.

This progression further intensified as the targeting of Chinese diplomatic activities transformed geopolitical tensions through pandemic-related content. Posts addressing interactions between international health organizations and the Chinese government consistently received higher anger reactions and engagement, such as "President Xi appreciated WHO Director-General's efforts," which achieved 458 angry reactions, and the post related to Xi's G20 Summit participation, which generated 1,166 angry reactions.

The most sophisticated rage-baiting operations found in the dataset relate to communal division and polarization. The controversy surrounding "Tablighi Jamaat" religious gathering coverage demonstrated systematic transformation of health concerns into communal blame targeting a particular community. User engagement metrics escalated significantly, especially for "Anger reactions," progressing from "Delhi: People show Covid-19 symptoms after religious gathering in Nizamuddin," which produced 1,716 angry reactions, to "Despite repetitive warnings to maintain social distance, over 10 people gathered to offer Namaz," which achieved 2,090 reactions.

Furthermore, class-based resentment was observed when political figures violated rules imposed during the COVID-19 period, generating higher angry responses compared to similar citizen violations, indicating exploitation of anti-establishment sentiment. The post about "BJP MLA Masala Jayaram celebrates birthday with 100 people amid lockdown" achieved 3,137 "Angry reactions," representing one of the highest single-post engagements for "Angry reactions." The most extreme responses were found in posts related to the Kolkata police incident, generating 3,667 angry reactions. This example of behavioral transgression demonstrates how power dynamic tensions can sustain heightened emotional activation.

The patterns observed in "healthcare worker discrimination" posts created powerful outrage and sustained high engagement. For instance, "Nurses and Doctors facing threats from landlords to vacate houses for being engaged in

Covid-19 treatments" received 1,129 angry reactions, while the post about "overworked medical professionals" achieved 1,439 reactions. These instances demonstrate how legitimate social concerns can be leveraged to maximize emotional intensity.

6.2 Potential Reasons for Unusual Patterns and Viral Content

The time series analysis reveals several examples of unusual patterns and sudden spikes in 'Facebook reactions' for major news outlets. These anomalies are based on different factors due to shifts in public sentiment, the viral content including major news events, etc.

Another notable example of public sentiment influencing engagement patterns was seen when the highest spike was shown in "angry" reactions for Hindustan Times on January 4, 2022, and the news was linked to a controversial information video about Mumbai airport. An Indian-origin man alleged that Mumbai airport's COVID test with the quarantine protocol was a "scam,". This post got 1,707 "Angry" reactions. This Spike of negative sentiment of users' frustrations and anger for the perceived injustices and mismanagement of Mumbai Airport during the pandemic crisis.

Similarly, a post about an Indian actor Sonu Sood, who took the initiative to help the students appearing for exams during the pandemic got the highest “Love” reactions from Hindustan Times on August 28, 2020.

On July 27, 2020, Hindustan Times covered Prime Minister Narendra Modi's claim that India was in a "much better situation" in the fight against COVID-19. This post received 4,311 "Haha" reactions, suggesting users found the claim ironic given India's challenges during the crisis.

These examples reveal controversial or emotionally charged news stories and public sentiments for them. These become viral content where the engagement level is characterized as extremely high due to its novelty, relevancy, or ability

to revoke strong public emotions. The presence of the celebrity-related cluster and the philanthropic cluster were the most positively received reactions with human interest stories having the ability and potential to be viral and social transmission on social media (Berger & Milkman, 2012).

The shifting of public sentiment with collective emotions can influence the pattern of engagement an example where The Indian Express post on October 16, 2020, with the feature of the post, was a migrant mother with her child as a representation of the goddess Durga (Indian mythological goddess) received 2,227 "Love" reactions; this positive response reflected the empathy of public and support for plight of migrant laborers during the COVID-19 crisis as well as the appreciation for their struggles.

6.3 Implications for News Outlets and Social Media Strategists

The findings sketch the importance of news content and social media strategies for news coverage during crises like the COVID-19 health emergency. News must be balanced in nature with informative reporting along with mindful emotions that may cover the story engaging and evoke sentiments; emphasizing the scientific progress, stories of community resilience, and effective policy responses may foster positive social discourse (Yavetz & Aharony, 2023). Influential public figures and their positive narrative can be an effective approach through social media to promote awareness of public health and encourage the public to adopt the guidelines regarding health issues (Wong et al., 2021).

The time series analysis highlights the importance of timely responsive communication and gives insight into how news media outlets should be prepared to meet the demand for information during the early stage of the crisis. This requires news outlets to utilize their resources for producing more content, fact-checking, and monitoring other social media to ensure the correctness and accuracy of information (Loecherbach et al., 2020).

The identification of “unusual patterns” and sudden spikes underscores the need to adapt to the rapid changes of the evolving situations for media outlets. Media houses should closely monitor the engagement metrics and be prepared to respond to the sudden spike in the activities. For example, the post related to Prime Minister Modi where he claimed that “the better situation” during the pandemic (Hindustan Times, July 27, 2020), generated a higher "Haha" reaction, indicating the need for a strategy to analyze and respond to public sentiment and the perception for the news.

Through the cluster analysis and topic modeling, the thematic diversity revealed the importance of the comprehensive coverage of new content, where the media outlets must strive to provide a balanced comprehensive news coverage of events or the health crisis with covering a wide range of topics and angles, this approach can help meet audiences' information needs (Gupta et al., 2021; Mach et al., 2021; Wang et al., 2024).

The sentiment analysis highlighted the emotional dimension for engaging and consuming the news content, thus social media and the news outlets' strategy should be more mindful to consider the impact of emotional content and their effects on audiences; they should try to provide the information in empathetic and constructive ways. It may involve a positive and solution-based narrative for reporting on challenges or hardships, early warning, monitoring infodemic and misinformation, and mitigating hatred and violence (Huang et al., 2022). For example, Cluster 3, "Philanthropic Responses to COVID-19 Pandemic," has a positive sentiment score which is related to a positive attitude toward the community's inspired hope and support during the COVID-19 crisis.

With the integration of advanced language models (GPT-4), it demonstrates the potential use of AI-assisted analysis. News media outlets should try to use these advanced tools to get a deeper insight into the audience sentiment, emergence of the trends, optimize content, and the impact of content (Colavito et al., 2024; Holmes et al., 2023).

While these implications offer valuable insights for news outlets and social media strategists, it is important to acknowledge the limitations of this study.

6.4 Limitations and Future Research Directions

This study provided valuable insight into users' engagement with "Facebook reaction" and their sentiment during the COVID-19 pandemic in India, it is important to know its limitations and identify scope for future research.

One of the biggest limitations is the focus on the major Indian news outlets, although these outlets are significantly leading the majority of outreach and high circulation in terms of print or social media, we can say they have captured a significant portion of the media landscape. However, they cannot capture the full diversity of news coverage and public sentiment of different areas and the population of the vast country. Future studies should expand and include regional and local news outlets for gathering a more comprehensive knowledge of the whole information ecosystem.

The "Facebook reactions" serve as a proxy for public sentiment. Reliance on them is a good indicator of emotional responses, though it cannot capture all the emotional complexity of audiences' attitudes and opinions. In the future, researchers can combine the "reaction" data with other resources such as user comments, texts, surveys, or interviews to get a more in-depth understanding of public sentiments (Anwar & Giglietto, 2024; Wahyuni & Budi, 2018).

The timeframe of this study ranges from March 24, 2020, to March 31, 2022, which covered almost a significant period of the COVID-19 pandemic in India. However, it could not capture in the long-term the evolution of users' sentiment and their engagement patterns and then after this cut-off date. In the future, it can extend the period and its later stages of the COVID-19 pandemic including the post-COVID-19 period: to know how the public discourse and their engagement through reactions evolve.

The usage of GPT-4 for labeling the clusters has a few limitations. These generated labels are based on a large language model's understanding of the provided input, which may not always be aligned together with human

understanding and interpretation of human perceptions. In the future, the validation of GPT-4 would be more robust with other techniques.

Lastly, this study is focused on India and the English language only, which have unique socio-cultural, economic-political, and media landscapes. Future research can be covered in different languages including comparing the different zones of India, or comparative studies between India and other countries, their similarities and differences in social media engagement and public sentiment during the pandemic (Bhattacharya et al., 2021).

Chapter 7: Conclusion

7.1 Summary of Key Findings

This study investigates the dynamics of Facebook engagement through "Facebook reactions" and public sentiment during the COVID-19 pandemic in India, focusing on four major media outlets: The Times of India, The Hindu, Indian Express, and Hindustan Times. Through a multi-method approach combining time series analysis, topic modeling, GPT-4 assisted cluster labeling, and sentiment analysis, this study revealed several key findings.

The time series analysis identified significant spikes in engagement during specific periods of the COVID-19 pandemic, followed by gradual declines over time. "Unusual days" and sudden changes in Facebook reactions were observed across all four news outlets, coinciding with major news events and viral posts. Topic modeling and cluster analysis revealed a diverse range of themes associated with COVID-19-related news coverage. The application of GPT-4 for cluster labeling demonstrated the potential of advanced language models to enhance the interpretability and coherence of topic modeling results. Twenty-five distinct thematic clusters were identified, reflecting various aspects of the COVID-19 pandemic's impact on India and the world.

Sentiment analysis revealed variations in emotional responses across different clusters and news outlets. The analysis identified distinct patterns of positive and negative sentiments, with positive sentiments associated with philanthropic responses and adaptations to daily life, while negative sentiments corresponded to global impact and lockdown enforcement measures. A moderate positive correlation emerged between news sentiment and user engagement.

The analysis demonstrated that different news outlets exhibited varying patterns of sentiment and user engagement, reflecting the influence of editorial policies, news content selection, target audience characteristics, and their role in shaping public discourse.

7.2 Contributions to the Field

This research makes many significant contributions to the field of crisis communication and social media. First, this study successfully integrates methodological innovations with multiple analytical approaches. The combination of sentiment analysis with Facebook reactions analysis provides a comprehensive approach to understanding public emotional responses. The novel application of GPT-4 for cluster labeling demonstrates how advanced large language models can enhance the analysis of social media-related big data. The development of a comprehensive engagement analysis framework, incorporating both time series analysis and topic modeling, contributes to a unique way to understand public response patterns during periods of crisis.

Second, the research advances theoretical frameworks in several ways: it enhances the understanding of crisis communication dynamics by revealing how emotions manifest on social media during the critical phase of the pandemic. This study also provides insight into social media and user engagement patterns, especially how different types of news content trigger emotional responses through Facebook reactions. Additionally, it enhances our understanding of public response mechanisms by demonstrating the relationship between user sentiment across news outlets.

Third, the study provides valuable practical applications for crisis management and social media strategies. It offers evidence-based guidelines for crisis management and communication, showing how different approaches to news coverage can influence public emotional responses. The developed framework for social media can help news media groups optimize and predict user engagement. Moreover, the metrics established for analyzing social media and user engagement offer practical tools for media organizations and researchers to assess public responses in future crises.

Collectively, these contributions advance our understanding of social media and its role in crises while providing theoretical frameworks and practical tools for future research. The study's emphasis on the Indian context during the COVID-19 pandemic, with a multi-method approach, provides unique insights into how social media platforms became indicators of public sentiment during global crises.

7.3 Recommendations and Concluding Remarks

Based on the study and findings, there are several recommendations can be present for effective communication during a crisis like the COVID-19 pandemic: Media outlets can focus on the topics that generate positive sentiment along with higher engagement such as “community support and philanthropic responses” which fosters a sense of hope and resilience during the ongoing crisis.

News outlets should make their content and communication strategies for their targeted audiences by having an account of sentiment and engagement across the different news outlets and platforms.

Social media strategists should pay attention to user reactions and their engagement to swift identification to address potential misinformation or controversial content. Government policy makers and other authorities should collaborate with media outlets and social media platforms to ensure the dissemination of information must be accurate and timely delivered to combat the spread of misinformation.

Researchers and media houses should develop and apply advanced computational methods, such as topic modeling and sentiment analysis and using AI to analyze big date related to social media platforms and enhance the prospective of insight into public discourse and information ecosystems during the crisis. The COVID-19 pandemic has underscored the importance of social media and media outlets in shaping public opinion and sentiment during global crises. This study examines the role of COVID-19 news coverage and public reactions on Facebook in India throughout the pandemic period. The multi-method approach employed demonstrates the effectiveness of advanced computational methods in analyzing social media data while providing a robust framework for future research. The findings reveal the complex interplay between content, emotions, and user engagement, offering practical guidelines for media organization policymakers and communications professionals. This study advances our understanding of crisis communication in the digital age and establishes a foundation for future research in this field.

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Entrepreneurship: Exploring the Unforeseen, and Paving the Way to a Sustainable Future, edited by Richard Adams, Dietmar Grichnik, Asta Pundziene and Christine Volkmann, 191–214. Cham: Springer International Publishing. doi: 10.1007/978-3-031-11371-0_9

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Appendices

Appendix A. Supplementary materials for systematic literature review

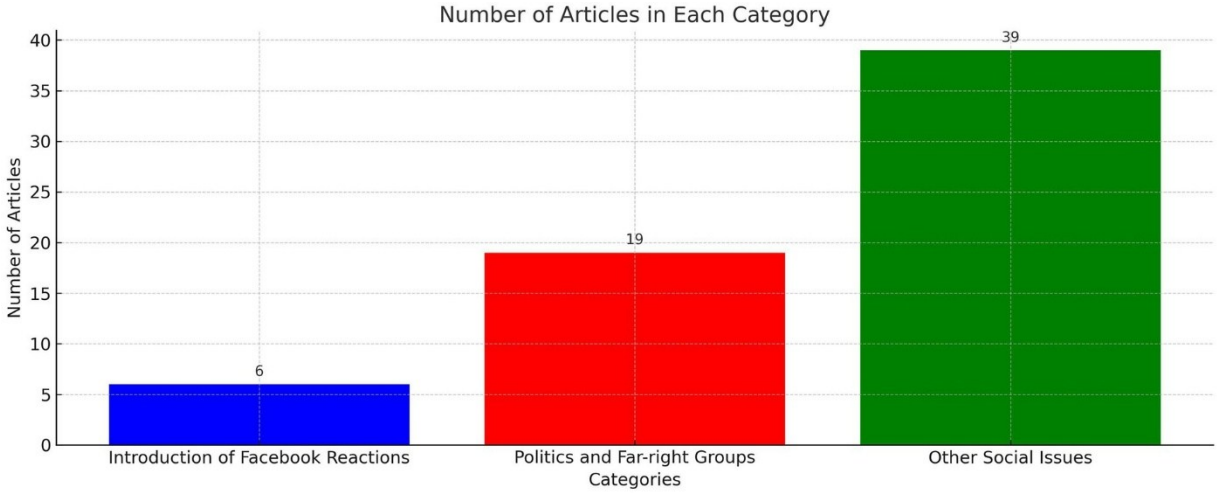


Figure 1 – *A total of 64 published articles analyzed between 2016 and 2023.*

Supplementary Material

The following supplementary tables catalog the entire dataset of 64 studies considered in this analysis. The dataset is divided into several categories as follows: Table 1: Introduction of Facebook Reactions (N=6), Table 2: Politics and Far-Right Groups Related Articles (N=19), Table 3a: Other Social Issues (Business and Customer Engagement) (N=6), Table 3b: Other Social Issues (Psychological, Sentimental, and Emotional) (N=17), Table 3c: Other Social Issues (Healthcare) (N=8), and Table 3d: Other Social Issues (Miscellaneous) (N=8). When available, a brief commentary is provided in the "Result and Observation" column.

Supplementary Tables

Articles	Result and Observation
Turnbull, S., & Jenkins, S. (2016). Why Facebook Reactions are good news for evaluating social media campaigns. *Journal*	An opportunity for

of Direct, Data and Digital Marketing Practice, *17*(3), 156–158. https://doi.org/10.1057/dddmp.2015.56	marketers to measure such emotional engagement.
Varanasi, R. A., Dicicco, E., & Gambino, A. (2018). Facebook Reactions: Impact of Introducing New Features of SNS on Social Capital. In C. Stephanidis (Ed.), *HCI International 2018 – Posters' Extended Abstracts* (Vol. 850, pp. 444–451). Springer International Publishing. https://doi.org/10.1007/978-3-319-92270-6_64	Help us understand the relationship maintenance, group cohesion,
ADDIN ZOTERO_BIBL {"uncited":[],"omitted":[],"custom":[]} CSL_BIBLIOGRAPHY Smoliarova, A., Gromova, T., & Pavlushkina, N. (2018). Emotional Stimuli in Social Media User Behavior: Emoji Reactions on a News Media Facebook Page. *Internet Science*, 242–256. https://doi.org/10.1007/978-3-030-01437-7_19	Love icon is used in the most mono-semantic way; Posts evoking a Sad reaction are less likely to be commented on or shared than posts arousing any other reaction
Wisniewski, P., Badillo-Urquiola, K., Ashtorab, Z., & Vitak, J. (2020). Happiness and Fear: Using Emotions as a Lens to Disentangle How Users Felt About the Launch of Facebook	After launch users were more

Reactions. *ACM Transactions on Social Computing*, *3*(4), 20:1-20:25. https://doi.org/10.1145/3414825	positive about the feature; users' inability to express conflicting emotions.
Merrill, J. B., & Oremus, will. (2021, October 26). *Five points for anger, one for a 'like': How Facebook's formula fostered rage and misinformation*. Washington Post. https://www.washingtonpost.com/technology/2021/10/26/facebook-angry-emoji-algorithm/	
Paolillo, J. C. (2023). The awkward semantics of Facebook reactions. *First Monday*. https://doi.org/10.5210/fm.v28i8.13157	The reactions' distribution is complex and unstable across samples.

Table - 1) *Introduction of Facebook Reactions*

Articles	Result and Observation
Turnbull, S., & Jenkins, S. (2016). Why Facebook Reactions are good news for evaluating social media	An opportunity for marketers to

campaigns. *Journal of Direct, Data and Digital Marketing Practice*, *17*(3), 156–158. https://doi.org/10.1057/dddmp.2015.56	measure such emotional engagement.
Larsson, A. (2017). Diversifying Likes—Relating Reactions to Commenting and Sharing on Newspaper Facebook Pages. *Journalism Practice*. https://doi.org/10.1080/17512786.2017.1285244	More positive forms of Reactions appear to have a hampering effect on the willingness of news consumers; more negative varieties of Facebook Reactions appear to yield adverse influences.
Basile, A., Caselli, T., Merenda, F., & Nissim, M. (2018). Facebook Reactions as Controversy Proxies: Predictive Models over Italian News. *Italian Journal of Computational Linguistics*, *4*(2), 73–89. https://doi.org/10.4000/ijcol.514	Controversy and reactions can be modeled successfully at various degrees of granularity.
Basile, A., Caselli, T., & Nissim, M. (2018). Predicting Controversial News Using Facebook Reactions. In R. Basili & G. Satta (Eds.), *Proceedings of the Fourth Italian Conference on Computational Linguistics CLiC-it 2017: 11-12 December 2017, Rome* (pp. 12–17). Accademia University Press. https://doi.org/10.4000/books.aaccademia.2370	Results are promising, given that the model beats the baseline in almost all cases in cross-validation of the same source data.
Keller, T. R., & Kleinen-von Königslöw, K. (2018). Followers, Spread the Message! Predicting the Success of Swiss Politicians on Facebook and Twitter. *Social*	Digital followership in turn influences the average number of

Media + Society, *4*(1), 2056305118765733. https://doi.org/10.1177/2056305118765733	digital reactions on Facebook.
Mancosu, M. (2018). Populism, Emotionalized Blame Attribution and Selective Exposure in Social Media. A Comparative Analysis of Italy and UK. *Comunicazione Politica*, *1*, 73–92. https://doi.org/10.3270/89738	Allows users to indicate the emotions that a post provokes in them (sadness, joy, anger, etc.).
Sandoval-Almazan, R., & Valle-Cruz, D. (2018). Facebook impact and sentiment analysis on political campaigns. *Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age*, 1–7. https://doi.org/10.1145/3209281.3209328	Facebook emoticons gave some approach to the perception of voter's sympathy or interest in the candidate.
Al-Rawi, A. (2019). Networked emotional news on social media. *Networked Emotional News on Social Media, Journalism Practice*, *14*(9), 1125–1141. https://doi.org/10.1080/17512786.2019.1685902	Readers are emotionally engaged with news that involves positive feelings, especially love.
Blassnig, S., & Wirz, D. S. (2019). Populist and Popular: An Experiment on the Drivers of User Reactions to Populist Posts on Facebook. *Social Media + Society*, *5*(4), 2056305119890062. https://doi.org/10.1177/2056305119890062	Users with strong populist attitudes share populist messages more often than they share non-populist messages.
Burger, P., Kanhai, S., Pleijter, A., & Verberne, S. (2019). The reach of commercially motivated junk news on Facebook. *PLOS ONE*, *14*(8), e0220446. https://doi.org/10.1371/journal.pone.0220446	Junk news pages have been increasingly successful in

	attracting user engagement.
Gerbaudo, P., Marogna, F., & Alzetta, C. (2019). When "Positive Posting" Attracts Voters: User Engagement and Emotions in the 2017 UK Election Campaign on Facebook. *Social Media + Society*, *5*(4), 2056305119881695. https://doi.org/10.1177/2056305119881695	Need for a more balanced understanding of the relationship between content, emotions, and user engagement.
Eberl, J.-M., Tolochko, P., Jost, P., Heidenreich, T., & Boomgaarden, H. (2020). What's in a post? How sentiment and issue salience affect users' emotional reactions on Facebook. *Journal of Information Technology & Politics*, *17*. https://doi.org/10.1080/19331681.2019.1710318	Effect of sentiment on "Angry" Reactions is highest.
Jost, P., Maurer, M., & Hassler, J. (2020). Populism Fuels Love and Anger: The Impact of Message Features on Users' Reactions on Facebook. *International Journal of Communication*, *14*(0), Article 0. https://doi.org/1932–8036/20200005	Love and Angry can be categorized as positive and negative one-click expressions of emotional states.
Sandoval-Almazan, R., & Valle-Cruz, D. (2020). Sentiment Analysis of Facebook Users Reacting to Political Campaign Posts. *Digital Government: Research and Practice*, *1*(2), 1–13. https://doi.org/10.1145/3382735	The winning political party had more negative sentiment.
Savolainen, L., Trilling, D., & Liotsiou, D. (2020). Delighting and Detesting Engagement: Emotional Politics of Junk News. *Social Media + Society*, *6*(4), 2056305120972037. https://doi.org/10.1177/2056305120972037	Junk news brings otherwise disparate audience members together and orients their dramatic focus toward objects of

	collective joy, anger, or concern.
de León, E., & Trilling, D. (2021). A Sadness Bias in Political News Sharing? The Role of Discrete Emotions in the Engagement and Dissemination of Political News on Facebook. *Social Media + Society*, *7*(4), 20563051211059710. https://doi.org/10.1177/20563051211059710	A negativity bias in news sharing and engagement shows an outsized prevalence of anger in response to political news.
Muraoka, T., Montgomery, J., Lucas, C., & Tavits, M. (2021). Love and Anger in Global Party Politics: Facebook Reactions to Political Party Posts in 79 Democracies. *Journal of Quantitative Description: Digital Media*, *1*, 1–38. https://doi.org/10.51685/jqd.2021.005	Parties receive systematically different proportions of Love and Angry reactions depending on their ideology, party family, and populist orientation.
Sturm Wilkerson, H., Riedl, M. J., & Whipple, K. N. (2021). Affective Affordances: Exploring Facebook Reactions as Emotional Responses to Hyperpartisan Political News. *Digital Journalism*, *9*(8), 1040–1061. https://doi.org/10.1080/21670811.2021.1899011	Analyze emotional reactions elicited through Facebook Reactions in response to right- and left-leaning Facebook news posts.
Zerback, T., & Wirz, D. S. (2021). Appraisal patterns as predictors of emotional expressions and shares on political social networking sites. *Studies in Communication Sciences*, *21*(1), Article 1. https://doi.org/10.24434/j.scoms.2021.01.003	If posts that include sadness or anger are associated with the corresponding emotional reactions in the form of

	emojis, these posts are shared more often.
Bagić Babac, M. (2022). Emotion analysis of user reactions to online news. *Information Discovery and Delivery*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/IDD-04-2022-0027	A comprehensive understanding of the engagement could be a better predictor of future behavior.
Bil-Jaruzelska, A., & Monzer, C. (2022). All About Feelings? Emotional Appeals as Drivers of User Engagement With Facebook Posts. *Politics and Governance*, *10*(1), 172–184. https://doi.org/10.17645/pag.v10i1.4758	Engagement with a post substantially increases when appeals to anger, enthusiasm, and pride are present; no relationship between appeals to fear and engagement.
Sandberg, L., Jacobs, K., & Spierings, N. (2022). Populist MPs on Facebook: Adoption and emotional reactions in Austria, the Netherlands, and Sweden. *Scandinavian Political Studies*, *45*(4), 504–528. https://doi.org/10.1111/1467-9477.12239	Facebook posts of populist MPs activate feelings of indignation, triggering more emotional responses; "haha" also reflects the sarcastic ridiculing of political opponents, paving the way for anger.
Klinger, U., Koc-Michalska, K., & Russmann, U. (2023). Are Campaigns Getting Uglier, and Who Is to	Populist content also led to more

Blame? Negativity, Dramatization and Populism on Facebook in the 2014 and 2019 EP Election Campaigns. *Political Communication*, *40*(3), 263–282. https://doi.org/10.1080/10584609.2022.2133198	user reactions, Negative, exaggerated, and sensationalized messaging therefore makes sense from a strategic perspective.
Kluknavská, A., Novotná, M., & Eisele, O. (2023). Fuming Mad and Jumping with Joy: Emotional Responses to Uncivil and Post-Truth Communication by Populist and Non-Populist Politicians on Facebook During the COVID-19 Crisis. *Mass Communication and Society*, *0*(0), 1–25. https://doi.org/10.1080/15205436.2023.2252396	Uncivil and post-truth message elements, affiliation with a populist party, and the pandemic Influenced the volume of emotional interactions with political posts.
Macdonald, M., Russell, A., & Hua, W. (2023). Negative Sentiment and Congressional Cue-Taking on Social Media. *PS: Political Science & Politics*, *56*(2), 201–206. https://doi.org/10.1017/S1049096522001299	New evidence demonstrates the power of that negative sentiment to elicit more user engagement.
Nip, J. Y. M., & Berthelier, B. (2023). Emotional Profiles of Facebook Pages: Audience Response to Political News in Hong Kong. *Journalism and Media*, *4*(4), Article 4. https://doi.org/10.3390/journalmedia4040065	The emotion most associated with their political news sharing.
Pérez-Seoane, J., Manuel Corbacho-Valencia, J., & Dafonte-Gómez, A. (2023). An analysis of the most	Interactions stem from emotional

viral posts from Ibero-American fact-checkers on Facebook in 2021. *Revista ICONO 14. Revista Científica de Comunicación y Tecnologías Emergentes*, *21*(1), 1–20. https://doi.org/10.7195/ri14.v21i1.1951	reactions, predominantly those associated with positive feelings.
Matamoros Fernandez, A. (2018). Inciting anger through Facebook reactions in Belgium: The use of emoji and related vernacular expressions in racist discourse. *First Monday*, *23*(9), Article 9.	Represent an opportunity to investigate the material politics of platforms and explore their role in racist discourse.
Tasente, T., & Rus, M. (2019). Donald Trump's Social Media Communication or the voice of a man is stronger than the voice of an institution. *Technium Social Sciences Journal*, *1*, 1–8. https://doi.org/10.47577/tssj.v1i1.27	Identified and analyzed the messages that generate high engagement from users; and the dominant reactions generated by the online audience.
Hutchinson, J., & Droogan, J. (2022). Far-right "Reactions": A comparison of Australian and Canadian far-right extremist groups on Facebook. *Behavioral Sciences of Terrorism and Political Aggression*. https://doi.org/10.1080/19434472.2022.2112742	Interpretation of far-right extremist themes and narrative and user engagement.
Gerbaudo, P., De Falco, C. C., Giorgi, G., Keeling, S., Murolo, A., & Nunziata, F. (2023). Angry Posts Mobilize: Emotional Communication and Online Mobilization in the Facebook Pages of Western European Right-Wing Populist Leaders. *Social Media + Society*, *9*(1), 20563051231163327. https://doi.org/10.1177/20563051231163327	Highlights that stoking public anger, especially around controversial issues such as

	immigration and security.
Hutchinson, J., & Droogan, J. (2023, January 30). More Than Just Pretty Pictures: A Comparison of Australian and Canadian Far-Right Extremist 'Reaction' Usage on Facebook. *GNET*. https://gnet-research.org/2023/01/30/more-than-just-pretty-pictures-a-comparison-of-australian-and-canadian-far-right-extremist-reaction-usage-on-facebook/	User's interpretation of extremist ideology.
Oliveira, L., & Azevedo, J. (2023). Using Social Media Categorical Reactions as a Gateway to Identify Hate Speech in COVID-19 News. *Sn Computer Science*, *4*(1), 11. https://doi.org/10.1007/s42979-022-01421-5	Negative emotions alone do not always indicate the presence of hate speech.

Table - 2) Politics and Far-right groups related Articles.

Articles
Krebs, F., Lubascher, B., Moers, T., Schaap, P., & Spanakis, G. (2017). *Social Emotion Mining Techniques for Facebook Posts Reaction Prediction* (arXiv:1712.03249). arXiv. https://doi.org/10.48550/arXiv.1712.03249
Antoniadis, I., Paltsoglou, S., & Patoulidis, V. (2019). Post popularity and reactions in retail brand pages on Facebook. *International Journal of Retail & Distribution Management*, *47*(9), 957–973. https://doi.org/10.1108/IJRDM-09-2018-0195
Lee, Y.-I., Phua, J., & Wu, T.-Y. (2020). Marketing a health Brand on Facebook: Effects of reaction icons and user comments on brand attitude, trust, purchase intention, and eWOM intention. *Health Marketing Quarterly*, *37*(2), 138–154. https://doi.org/10.1080/07359683.2020.1754049
Yang, M., Ren, Y., & Adomavicius, G. (2020). Engagement by Design: An Empirical Study of the "Reactions" Feature on Facebook Business Pages. *ACM Transactions on Computer-Human Interaction*, *27*(6), 1–35. https://doi.org/10.1145/3412844

Dehouche, N. (2020). Dataset on usage and engagement patterns for Facebook Live sellers in Thailand. *Data in Brief*, *30*, 105661. https://doi.org/10.1016/j.dib.2020.105661
Vaiciukynaite, E., Zickute, I., & Salkevicius, J. (2022). *Solutions of Brand Posts on Facebook to Increase Customer Engagement Using the Random Forest Prediction Model* (pp. 191–214). https://doi.org/10.1007/978-3-031-11371-0_9

Table – 3a) *Other Social Issues (Business and customer engagement)*

Articles
Pool, C., & Nissim, M. (2016). *Distant supervision for emotion detection using Facebook reactions* (arXiv:1611.02988). arXiv. https://doi.org/10.48550/arXiv.1611.02988
Tian, Y., Galery, T., Dulcinati, G., Molimpakis, E., & Sun, C. (2017). Facebook sentiment: Reactions and Emojis. *Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media*, 11–16. https://doi.org/10.18653/v1/W17-1102
Kuo, P. C., Alvarado, F. H. C., & Chen, Y.-S. (2018). *Facebook Reaction-Based Emotion Classifier as Cue for Sarcasm Detection* (arXiv:1805.06510). arXiv. https://doi.org/10.48550/arXiv.1805.06510
Raad, B. T., Philipp, B., Patrick, H., & Christoph, M. (2018). ASEDS: Towards Automatic Social Emotion Detection System Using Facebook Reactions. *2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, 860–866. https://doi.org/10.1109/HPCC/SmartCity/DSS.2018.00143
Giuntini, F. T., Ruiz, L. P., Kirchner, L. D. F., Passarelli, D. A., Dos Reis, M. D. J. D., Campbell, A. T., & Ueyama, J. (2019). How Do I Feel? Identifying Emotional Expressions on Facebook Reactions Using Clustering Mechanism.

IEEE Access, *7*, 53909–53921. https://doi.org/10.1109/ACCESS.2019.2913136

Freeman, C., Roy, M. K., Fattoruso, M., & Alhoori, H. (2019). Shared Feelings: Understanding Facebook Reactions to Scholarly Articles. *2019 ACM/IEEE Joint Conference on Digital Libraries (JCDL)*, 301–304. https://doi.org/10.1109/JCDL.2019.00050

Rahman, M. A., & Seddiqui, M. H. (2019). *Comparison of Classical Machine Learning Approaches on Bangla Textual Emotion Analysis* (arXiv:1907.07826). arXiv. https://doi.org/10.48550/arXiv.1907.07826

Graziani, L., Melacci, S., & Gori, M. (2019). *Jointly Learning to Detect Emotions and Predict Facebook Reactions* (arXiv:1909.10779). arXiv. https://doi.org/10.48550/arXiv.1909.10779

Freeman, C., Alhoori, H., & Shahzad, M. (2020). Measuring the Diversity of Facebook Reactions to Research. *Proceedings of the ACM on Human-Computer Interaction*, *4*(GROUP), 1–17. https://doi.org/10.1145/3375192

Geboers, M., Stolero, N., Scuttari, A., Vliet, L. V., & Ridley, A. (2020). Why Buttons Matter: Repurposing Facebook's Reactions for Analysis of the Social Visual. *International Journal of Communication*, *14*(2020), Article 0.

Wisniewski, P., Badillo-Urquiola, K., Ashtorab, Z., & Vitak, J. (2020). Happiness and Fear: Using Emotions as a Lens to Disentangle How Users Felt About the Launch of Facebook Reactions. *ACM Transactions on Social Computing*, *3*(4), 20:1-20:25. https://doi.org/10.1145/3414825

Scott, G. G., Conlon, L. J., & Wilson, C. (2020). Facebook Reactions: How are They Used and Which Personality Factors Predict their Use? *The Journal of Social Media in Society*, *9*(2), Article 2.

Jayawickrama, V., Weeraprameshwara, G., de Silva, N., & Wijeratne, Y. (2022). Facebook for Sentiment Analysis: Baseline Models to Predict Facebook Reactions of Sinhala Posts. *The International Journal on Advances in ICT for Emerging Regions*, *15*(2), 22–32.

Pratama, A. (2022). Sentiment Analysis of Facebook Posts through Special Reactions: The Case of Learning from Home in Indonesia Amid COVID-19. *Jurnal Ilmiah Teknik Elektro Komputer Dan Informatika (JITEKI)*, *8*(1), 83–92. https://doi.org/10.26555/jiteki.v8i1.23615

Chin, C.-Y., & Huang, W.-Y. (2023). Discovering fans and anti-fans among social media users based on their emotional reactions and comments. *Journal of Information Science*, 01655515231162284. https://doi.org/10.1177/01655515231162284
Shahzad, M., Freeman, C., Rahimi, M., & Alhoori, H. (2023). Predicting Facebook sentiments towards research. *Natural Language Processing Journal*, *3*, 100010. https://doi.org/10.1016/j.nlp.2023.100010
Paletz, S. B. F., Johns, M. A., Murauskaite, E. E., Golonka, E. M., Pandža, N. B., Rytting, C. A., Buntain, C., & Ellis, D. (2023). Emotional content and sharing on Facebook: A theory cage match. *Science Advances*, *9*(39), eade9231. https://doi.org/10.1126/sciadv.ade9231

Table – 3b) Other Social Issues (Psychological, Sentimental and Emotional)

Articles
Tran, T., Nguyen, D., Nguyen, A., & Golen, E. (2018). Sentiment analysis of marijuana content via Facebook emoji-based reactions. *2018 IEEE International Conference on Communications (ICC)*, 1–6. https://doi.org/978-1-5386-3180-5/18
Balakrishnan, V., Govindan, V., Arshad, N. I., Shuib, L., & Cachia, E. (2019). Facebook User Reactions and Emotion: An Analysis of Their Relationships among the Online Diabetes Community. *Malaysian Journal of Computer Science*, *Special Issue 2019*(Industrial Revolution: Impact and Readiness Special Issue, 2019), 87–97. https://doi.org/10.22452/mjcs.sp2019no3.6
Pócs, D., Adamovits, O., Watti, J., Kovács, R., & Kelemen, O. (2021). Facebook Users' Interactions, Organic Reach, and Engagement in a Smoking Cessation Intervention: Content Analysis. *Journal of Medical Internet Research*, *23*(6), e27853. https://doi.org/10.2196/27853
Hrincu, V., An, Z., Joseph, K. A., Jiang, Y. F., Shi, E., & Robillard, J. M. (2022). Dementia Research Engagement on Social Media: A Content

Analysis. *Alzheimer's & Dementia*, *18*(S8), e060826. https://doi.org/10.1002/alz.060826
Rovetta, A. (2022). World Health Organization is losing online credibility towards health-sensitive topics: Infodemiological analysis of Facebook users' reactions. *Health Promotion Perspectives*, *12*(4), 367–371. https://doi.org/10.34172/hpp.2022.48
Kilgo, D. K., & Midberry, J. (2022). Social Media News Production, Emotional Facebook Reactions, and the Politicization of Drug Addiction. *Health Communication*, *37*(3), 375–383. https://doi.org/10.1080/10410236.2020.1846265
Watti, J., Millner, M., Siklósi, K., Kiss, H., Kelemen, O., & Pócs, D. (2022). Smokers' Engagement Behavior on Facebook: Verbalizing and Visual Expressing the Smoking Cessation Process. *International Journal of Environmental Research and Public Health*, *19*(16), 9983. https://doi.org/10.3390/ijerph19169983
Yavetz, G., & Aharony, N. (2023). Information under lockdown: A content analysis of government communication strategies on Facebook during the COVID-19 outbreak. *Heliyon*, *9*(4), e15562. https://doi.org/10.1016/j.heliyon.2023.e15562

Table – 3c) *Other Social Issues (HealthCare)*

Articles
Ross, B., Potthoff, T., Majchrzak, T. A., Chakraborty, N. R., Ben Lazreg, M., & Stieglitz, S. (2018, January 3). *The Diffusion of Crisis-Related Communication on Social Media: An Empirical Analysis of Facebook Reactions*. 51st Hawaii International Conference on System Sciences |. http://hdl.handle.net/10125/50207
Oliveira, L., & Azevedo, J. (2021). Profiling Media Outlets and Audiences on Facebook: COVID-19 Coverage, Emotions and Controversy. *Proceedings of*

the 17th International Conference on Web Information Systems and Technologies, 186–196. https://doi.org/10.5220/0010717400003058
Masullo, G. M. (2022). Facebook reactions as heuristics: Exploring relationships between reactions and commenting frequency on news about COVID-19. *First Monday*.
Al-Zaman, Md. S., & Ahona, T. (2022). Users' Reactions to Rape News Shared on Social Media: An Analysis of Five Facebook Reaction Buttons. *Asian Journal for Public Opinion Research*, *10*, 51–73. https://doi.org/10.15206/ajpor.2022.10.1.51
Cantrell, S. J., Winters, R. M., Kaini, P., & Walker, B. N. (2022). Sonification of Emotion in Social Media: Affect and Accessibility in Facebook Reactions. *Proceedings of the ACM on Human-Computer Interaction*, *6*(CSCW1), 1–26. https://doi.org/10.1145/3512966
Johnson, C. (2023). *Courts Are Going to "Love" This: An Analysis of the Facebook "Reactions" as Hearsay* (SSRN Scholarly Paper 4364581). https://doi.org/10.2139/ssrn.4364581
Etta, G., Sangiorgio, E., Marco, N. D., Avalle, M., Scala, A., Cinelli, M., & Quattrociocchi, W. (2023). Characterizing engagement dynamics across topics on Facebook. *PLOS ONE*, *18*(6), e0286150. https://doi.org/10.1371/journal.pone.0286150
Cui, Y., Fang, Z., & Wang, X. (2023). Article promotion on Twitter and Facebook: A case study of Cell journal. *Journal of Information Science*, *49*(5), 1218–1228. https://doi.org/10.1177/01655515211059772

Table – 3d) *Other Social Issues (Miscellaneous)*

Appendix B. The COVID-19 News Coverage Reaction Analysis for Time series.

This appendix contains the R code used to analyze Facebook reactions to COVID-19 coverage across four Indian news.

The analysis covers the period from March 24, 2020 (beginning of India's first nationwide lockdown) to March 31, 2022.

Required R Libraries

```
library(dplyr)      # For data manipulation
library(ggplot2)    # For data visualization
library(zoo)        # For time series analysis
library(readr)      # For CSV file operations
library(lubridate)  # For date handling
library(scales)     # For plot formatting
```

Code Implementation

1. Data Import and Preprocessing

```
# Define reaction types
reactions <- c("like", "love", "wow", "haha", "sad", "angry", "care")


# Main analysis function
analyze_reaction <- function(data, reaction, outlet) {
   [Previous function code here]
}
```

2. Analysis Function

```
# Define reaction types
reactions <- c("like", "love", "wow", "haha", "sad", "angry", "care")


# Main analysis function
analyze_reaction <- function(data, reaction, outlet) {
  [Previous function code here]
}
```

3. Execution Code

```
# Perform analysis for each outlet and reaction
outlets <- unique(df$account.name)
for (outlet in outlets) {
  outlet_data <- filter(df, account.name == outlet)
  for (reaction in reactions) {
    analyze_reaction(outlet_data, reaction, outlet)
  }
}
```

Complete R Implementation

```
#==========================================================
========================
# Required Libraries
#==========================================================
========================
library(dplyr)      # For data manipulation
library(ggplot2)    # For data visualization
library(zoo)        # For time series analysis
library(readr)      # For CSV file operations
library(lubridate)  # For date handling
library(scales)     # For plot formatting

#==========================================================
========================
# File Path Definitions
#==========================================================
========================
file_path1 <-
"C:\\Users\\sawoo\\Desktop\\Analysis_COVID_19\\Indian_4_News_outlets_
Covid-19_Whole_Range_2020-03-24--2022-03-
31\\Time_month_week_day\\2024-07-07-12-07-02-CEST-Historical-Report-
Multiple-Pages-2020-03-24--2022-03-31.csv"
file_path2 <-
"/Users/sawoo/Desktop/Analysis_COVID_19/Indian_4_News_outlets_Covid-
19_Whole_Range_2020-03-24--2022-03-31/Time_month_week_day/2024-
```

```
07-07-12-07-02-CEST-Historical-Report-Multiple-Pages-2020-03-24--2022-
03-31.csv"

#=========================================================
========================
# Data Import with Error Handling
#=========================================================
========================
df <- tryCatch(
  read_csv(file_path1),
  error = function(e) {
    tryCatch(
      read_csv(file_path2),
      error = function(e) {
        stop("Error reading the CSV file. Please check the file path.")
      }
    )
  }
)

# Create Date column
df$Date <- as.Date(df$`Post Created Date`)

#=========================================================
========================
```

```
# Define Reaction Types
#==========================================================
=========================
reactions <- c("like", "love", "wow", "haha", "sad", "angry", "care")

#==========================================================
=========================
# Main Analysis Function
#==========================================================
=========================
analyze_reaction <- function(data, reaction, outlet) {
  # Map reaction names to column names
  reaction_col <- paste0("statistics.actual.", reaction, "Count")

  # Ensure the reaction column exists
  if (!(reaction_col %in% names(data))) {
    cat("Column", reaction_col, "not found for", outlet, "\n")
    return(NULL)
  }

  # Calculate daily statistics
  data <- data %>%
    arrange(Date) %>%
    group_by(Date) %>%
    summarize(reaction_count = sum(!!sym(reaction_col))) %>%
```

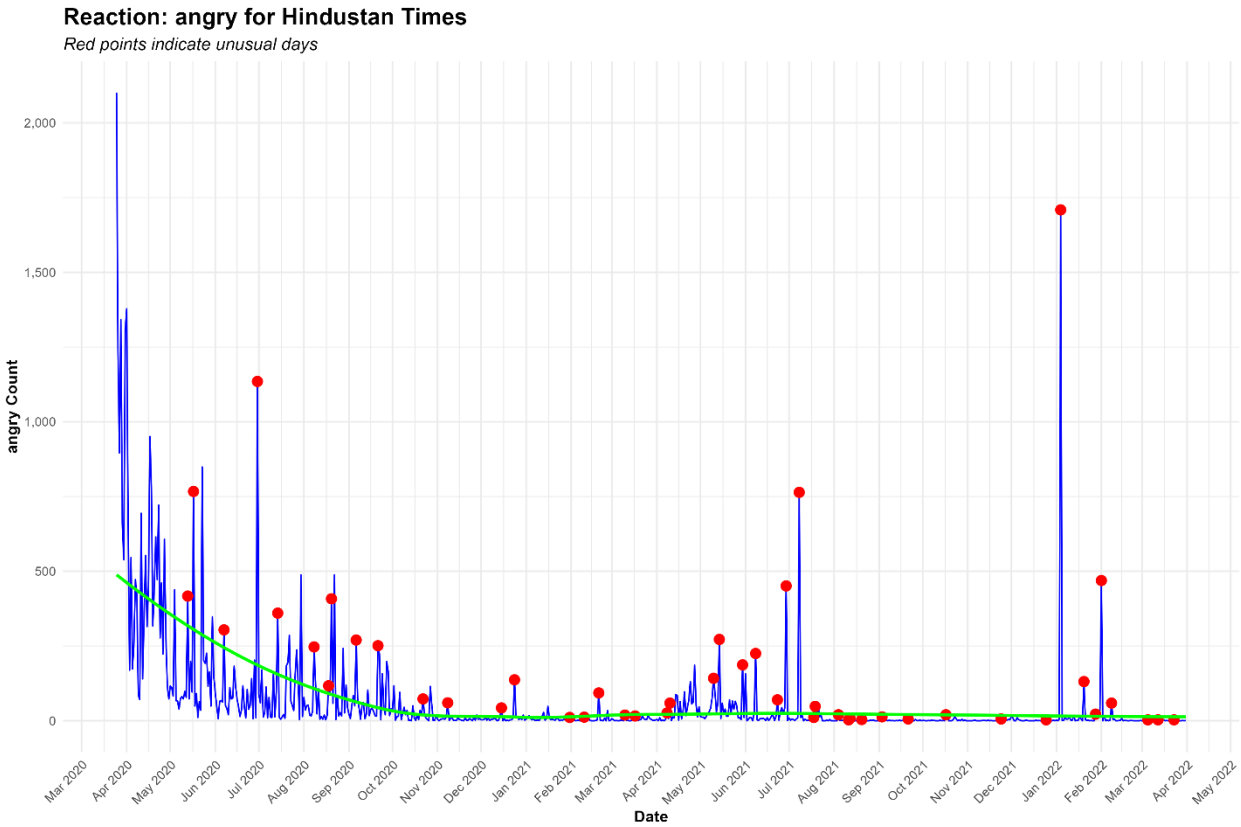
```
    ungroup() %>%
    mutate(
        diff = reaction_count - lag(reaction_count),
        pct_change = (diff / lag(reaction_count)) * 100
    )

# Calculate rolling statistics
data$rolling_mean <- rollmean(data$reaction_count, k = 7,
                              fill = NA, align = "right")
data$rolling_sd <- rollapply(data$reaction_count, width = 7,
                             FUN = sd, fill = NA, align = "right")

# Calculate z-scores
data$z_score <- (data$reaction_count - data$rolling_mean) / data$rolling_sd

# Define thresholds for unusual days
z_score_threshold <- 2
pct_change_threshold <- quantile(abs(data$pct_change), 0.95, na.rm =
TRUE)

# Identify unusual days
data$unusual <- abs(data$z_score) > z_score_threshold |
                abs(data$pct_change) > pct_change_threshold

# Get top changes
```

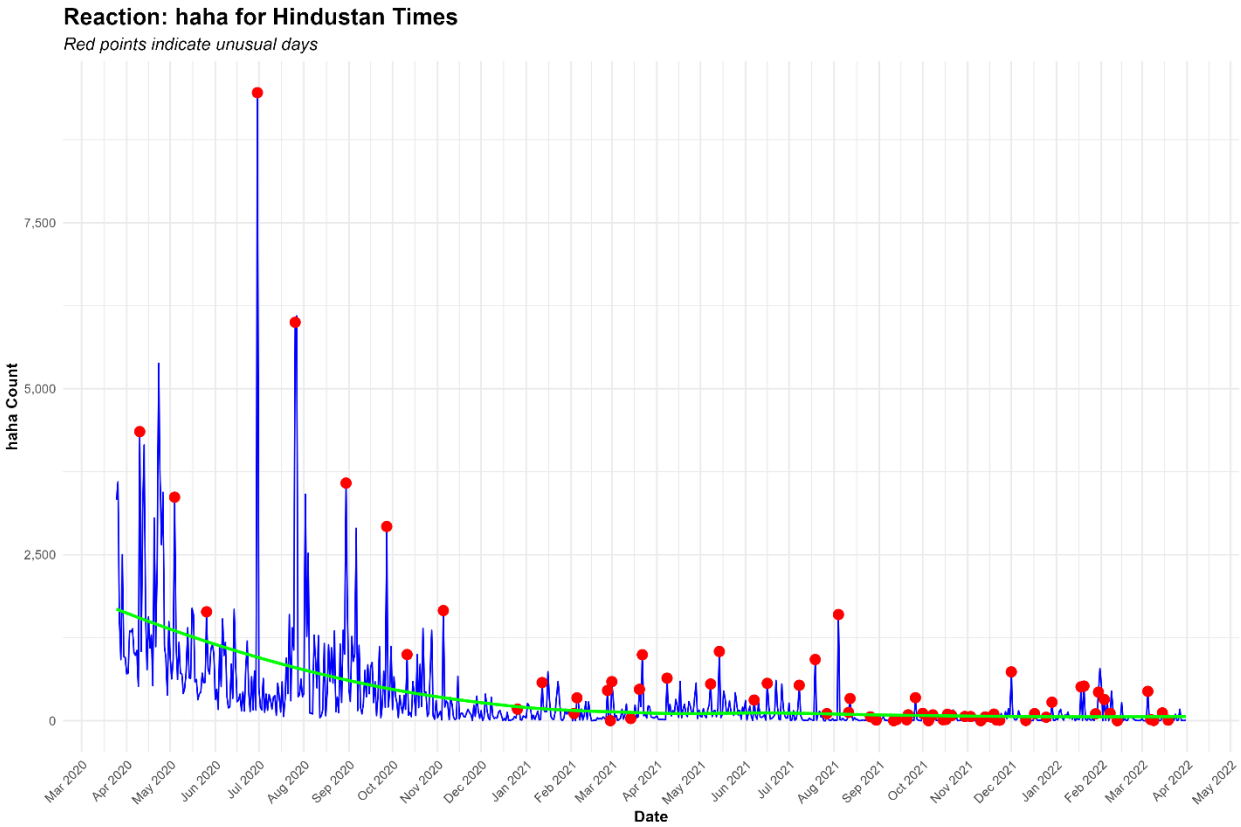
```
top_changes <- data %>%
    arrange(desc(abs(pct_change))) %>%
    head(5)



# Extract unusual days
unusual_days <- data %>%
    filter(unusual) %>%
    select(Date, reaction_count, z_score, pct_change)



#=========================================================
========================
# Create Visualization

#=========================================================
========================
p <- ggplot(data, aes(x = Date, y = reaction_count)) +
    # Base line
    geom_line(color = "blue", size = 0.5) +
    # Unusual days points
    geom_point(data = unusual_days, color = "red", size = 3) +
    # Trend line
    geom_smooth(method = "loess", color = "green", se = FALSE, size = 1) +
    # Labels and titles
```

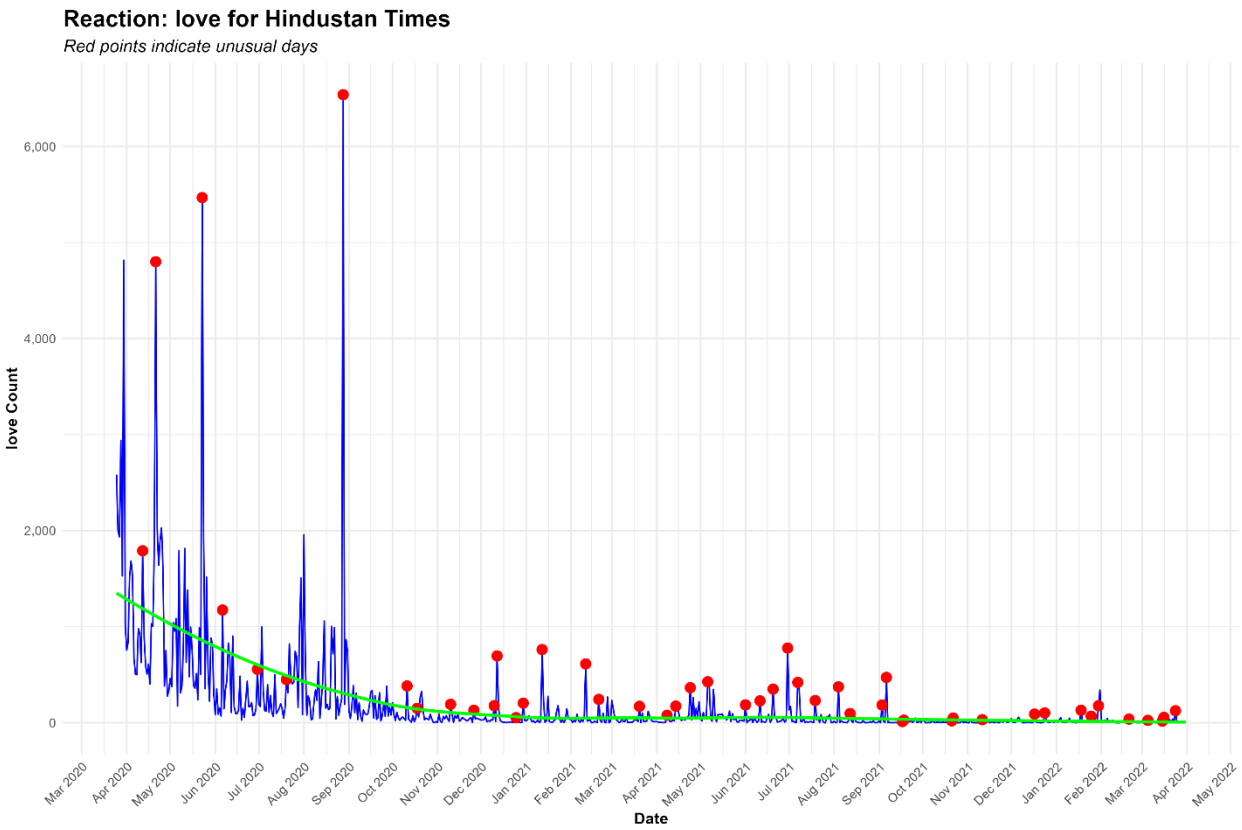
```
    labs(title = paste("Reaction:", reaction, "for", outlet),
         subtitle = "Red points indicate unusual days",
         x = "Date",
         y = paste(reaction, "Count")) +



    # Theme customization
    theme_minimal() +
    theme(
      plot.title = element_text(face = "bold", size = 16),
      plot.subtitle = element_text(face = "italic", size = 12),
      axis.title = element_text(face = "bold"),
      axis.text.x = element_text(angle = 45, hjust = 1)
    ) +
    # Scale customization
    scale_x_date(date_breaks = "1 month", date_labels = "%b %Y") +
    scale_y_continuous(labels = comma_format())



#=========================================================
========================
  # Save Outputs


#=========================================================
========================
```

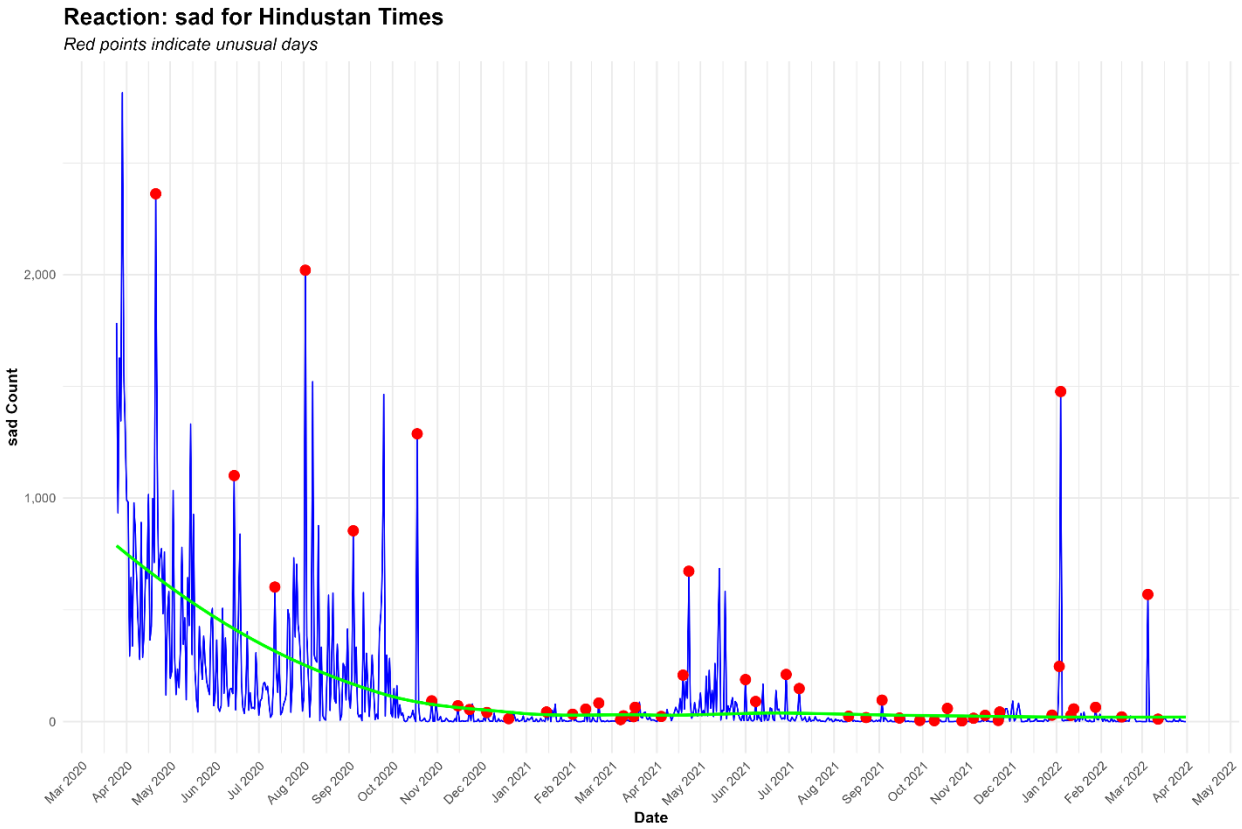
```
    # Save plot
    ggsave(paste0(outlet, "_", reaction, "_plot.png"),
           p, width = 12, height = 8, dpi = 300)

    # Save daily analysis
    write_csv(data, paste0(outlet, "_", reaction, "_analysis.csv"))



    # Save unusual days report
    if (nrow(unusual_days) > 0) {
      unusual_days_with_url <- unusual_days %>%
          mutate(URL = paste0("https://www.facebook.com/", outlet, "/posts/",
Date))
      write_csv(unusual_days_with_url,
                paste0(outlet, "_", reaction, "_unusual_days.csv"))
      cat("Unusual days file created for", reaction, "reaction of", outlet, "\n")
    } else {
      cat("No unusual days found for", reaction, "reaction of", outlet, "\n")
    }



#==========================================================
=========================

    # Print Results
```

```
#=========================================================
========================
  cat("\nAnalysis for", reaction, "reaction of", outlet, "\n")
  cat("\nTop 5 Sudden Changes:\n")
  print(top_changes[, c("Date", "reaction_count", "diff", "pct_change")])
  cat("\nUnusual Days:\n")
  print(unusual_days)
}

#=========================================================
========================
# Execute Analysis
#=========================================================
========================
# Get unique outlets
outlets <- unique(df$account.name)

# Run analysis for each outlet and reaction combination
for (outlet in outlets) {
  outlet_data <- filter(df, account.name == outlet)
  for (reaction in reactions) {
    analyze_reaction(outlet_data, reaction, outlet)
  }
}
```


Reaction: angry for Hindustan Times
Red points indicate unusual days
angry Count
2,000
1,500
1,000
500
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: haha for Hindustan Times
Red points indicate unusual days
haha Count
7,500
5,000
2,500
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: love for Hindustan Times
Red points indicate unusual days
love Count
6,000
4,000
2,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: sad for Hindustan Times
Red points indicate unusual days
sad Count
2,000
1,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date

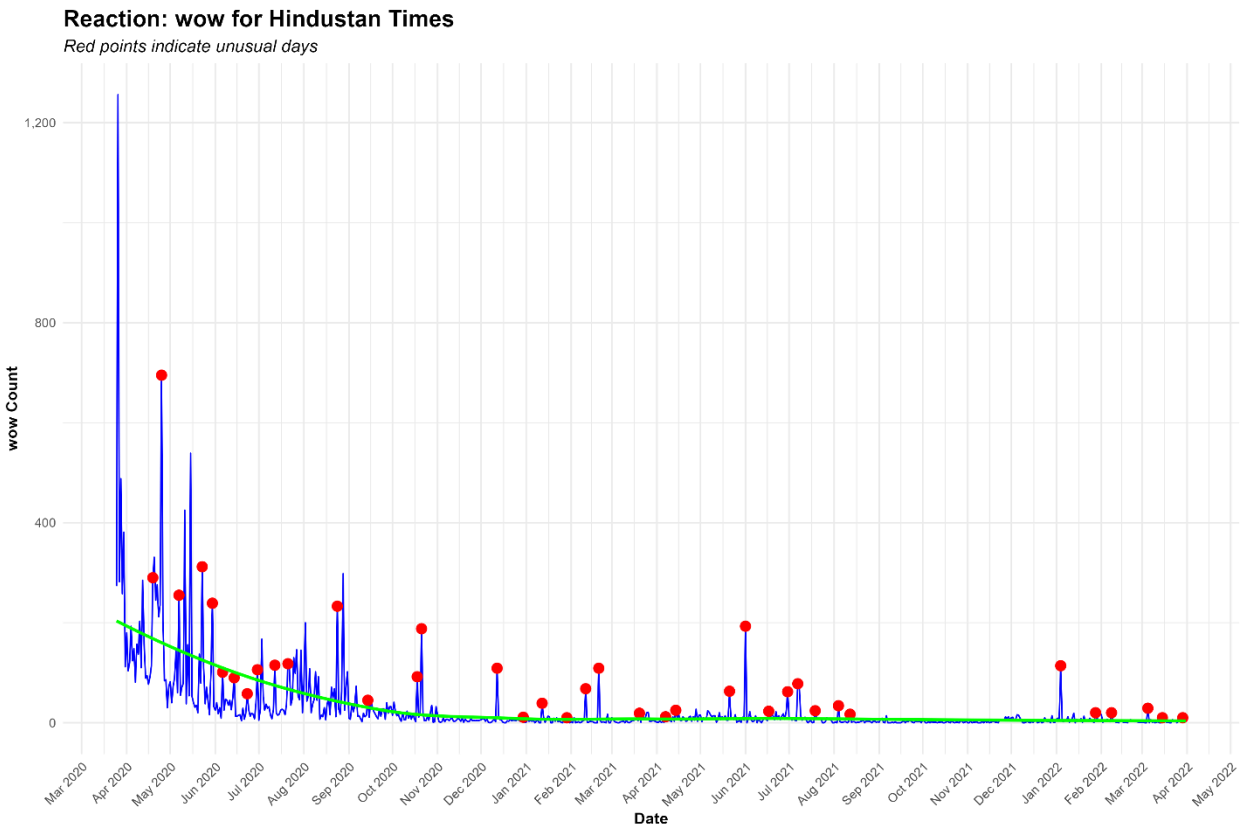
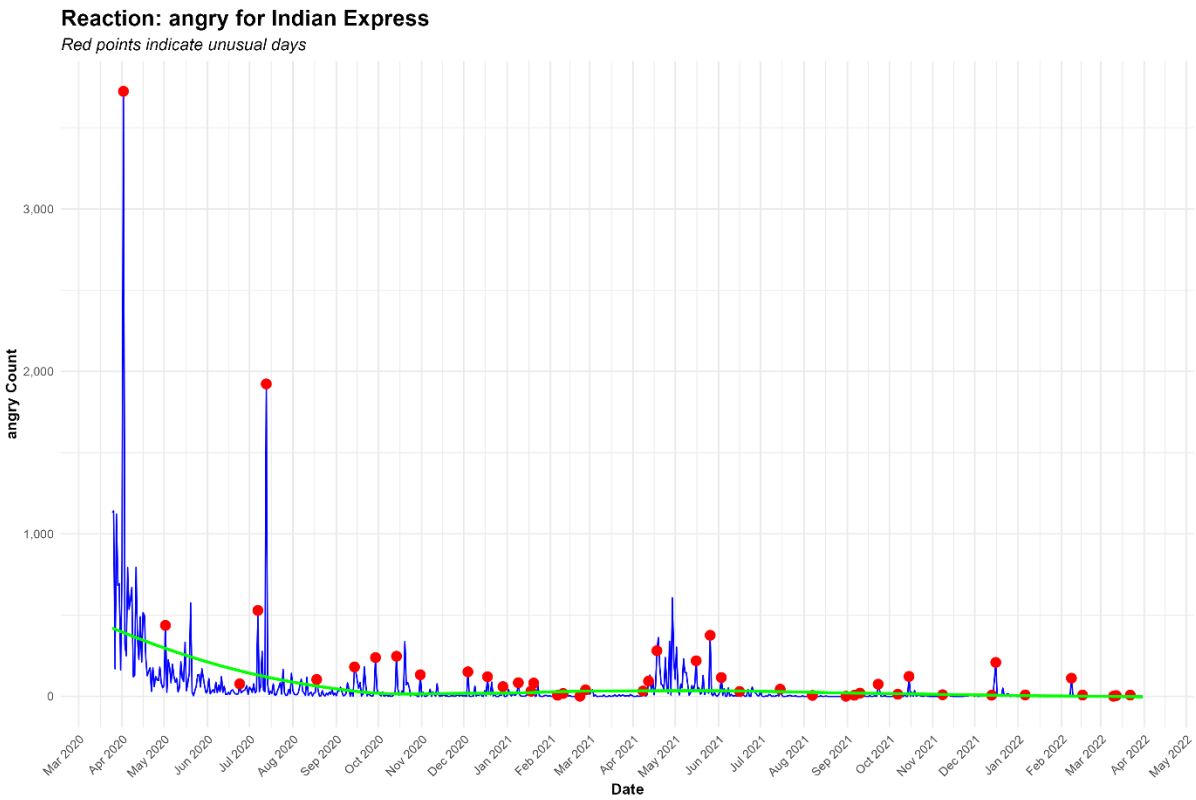
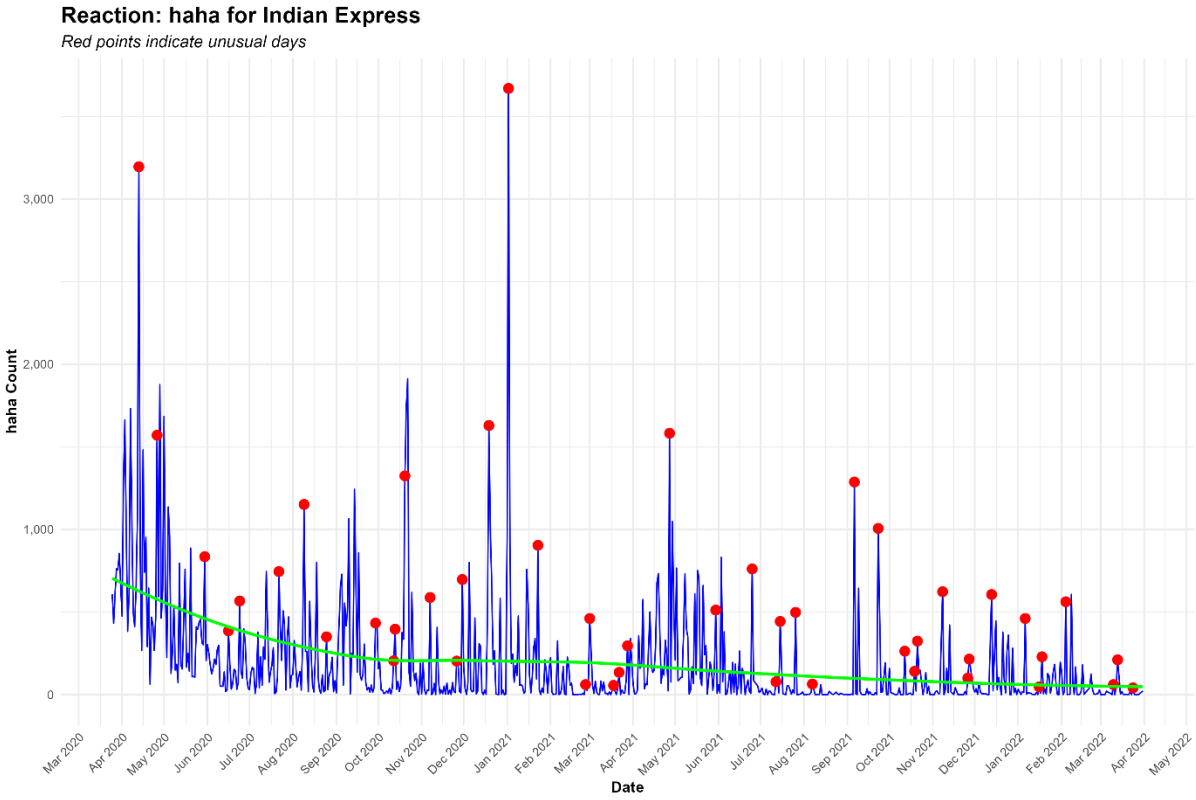
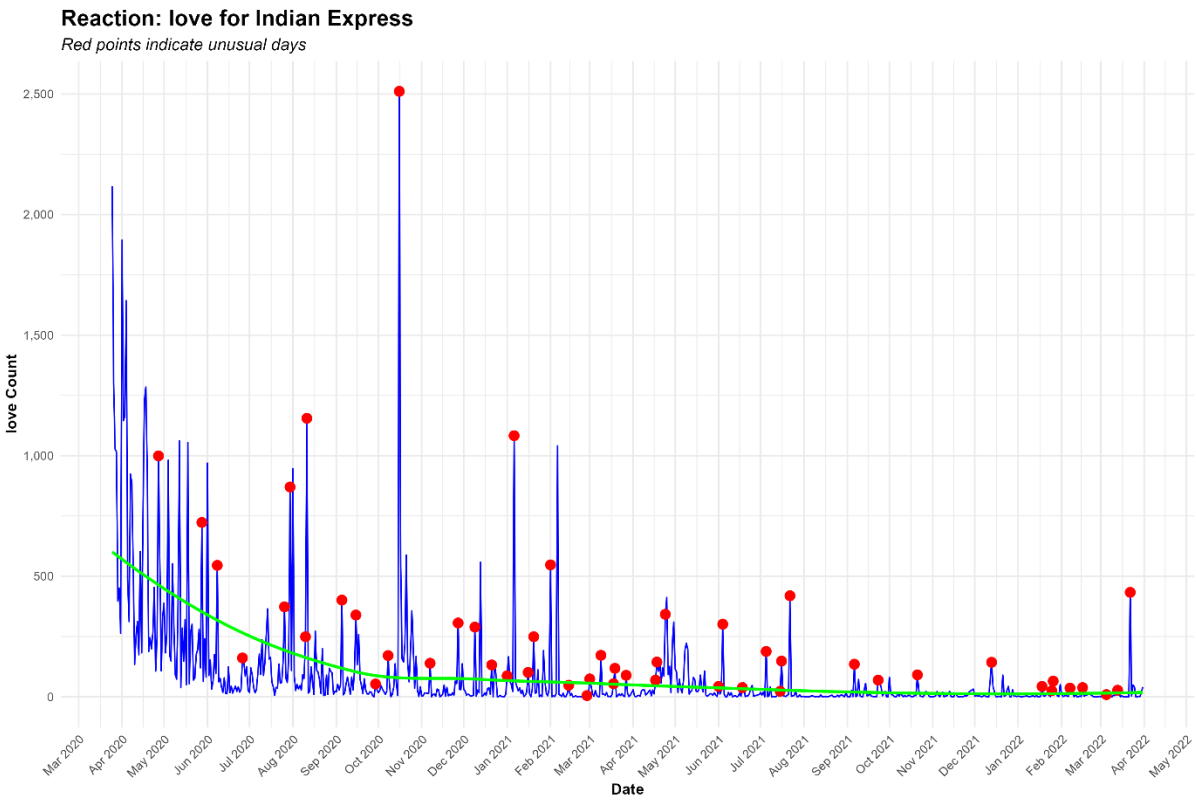
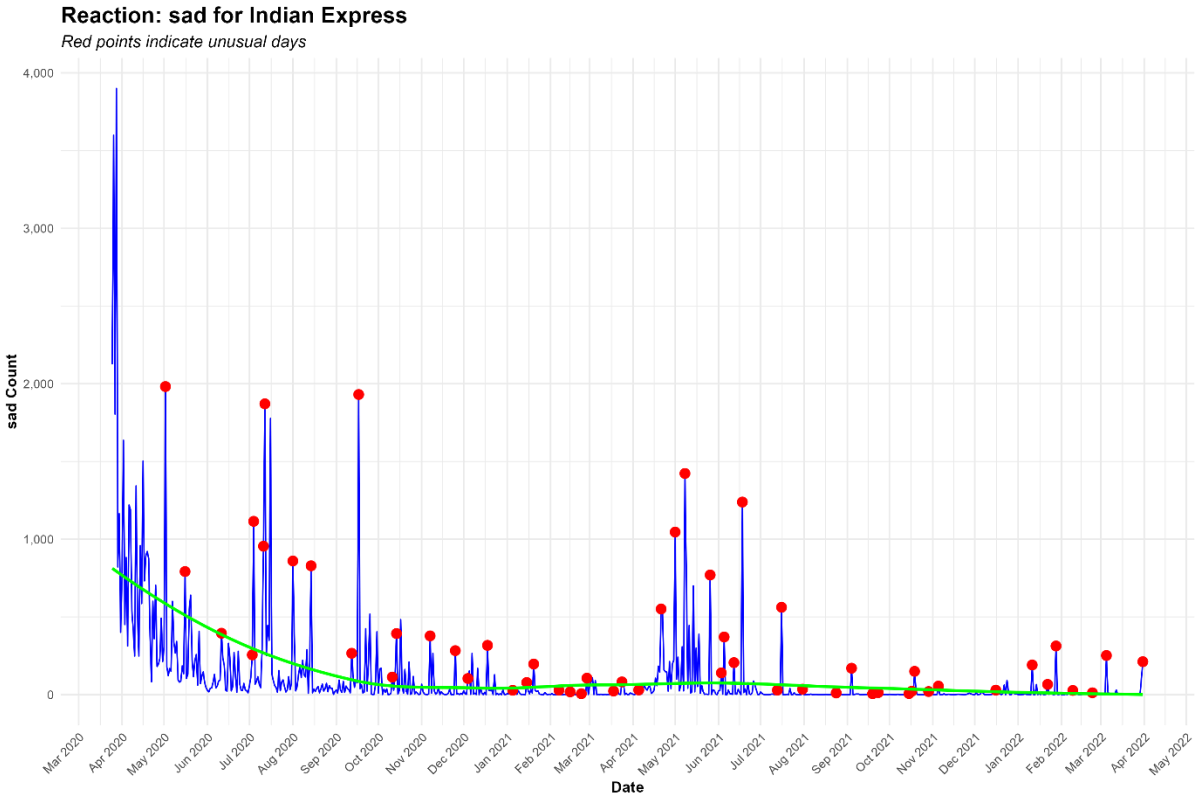


Figure 1 - *Unusual days for Hindustan Times with all Reactions*


Reaction: angry for Indian Express
Red points indicate unusual days
angry Count
3,000
2,000
1,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: haha for Indian Express
Red points indicate unusual days
haha Count
3,000
2,000
1,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: love for Indian Express
Red points indicate unusual days
love Count
2,500
2,000
1,500
1,000
500
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: sad for Indian Express
Red points indicate unusual days
sad Count
4,000
3,000
2,000
1,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
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Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date

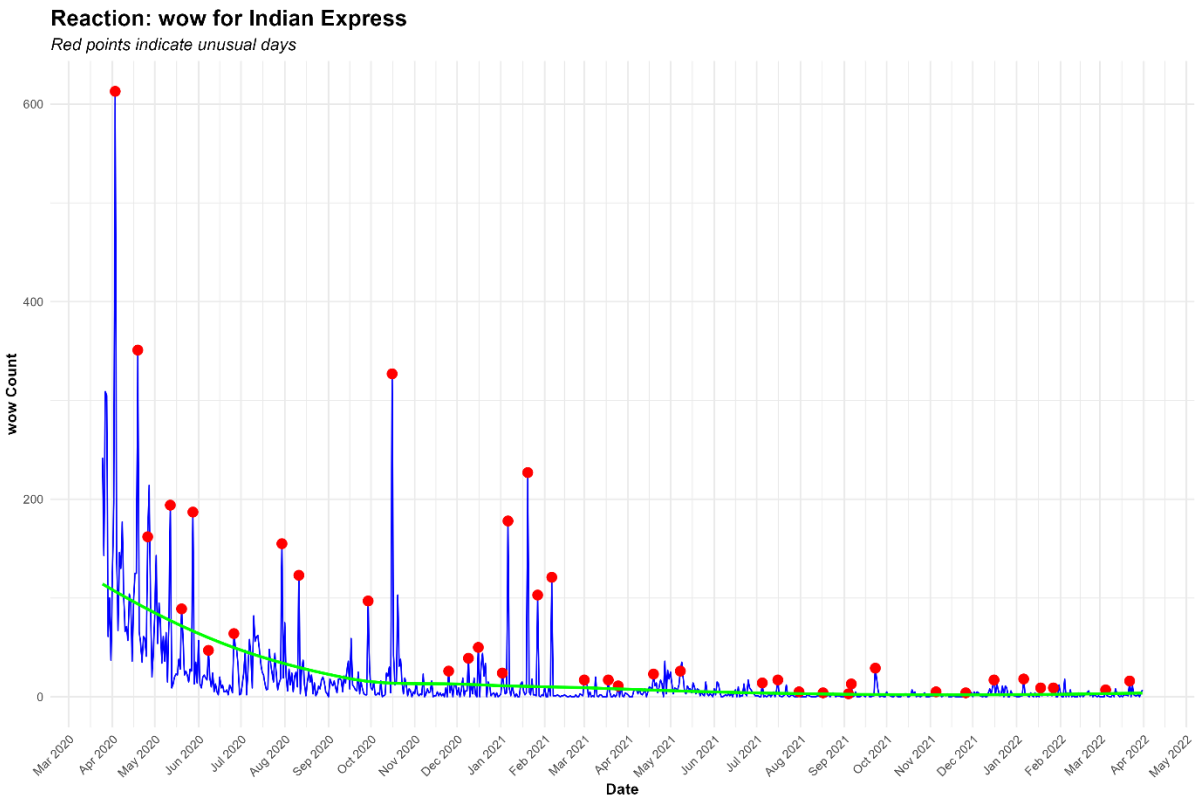
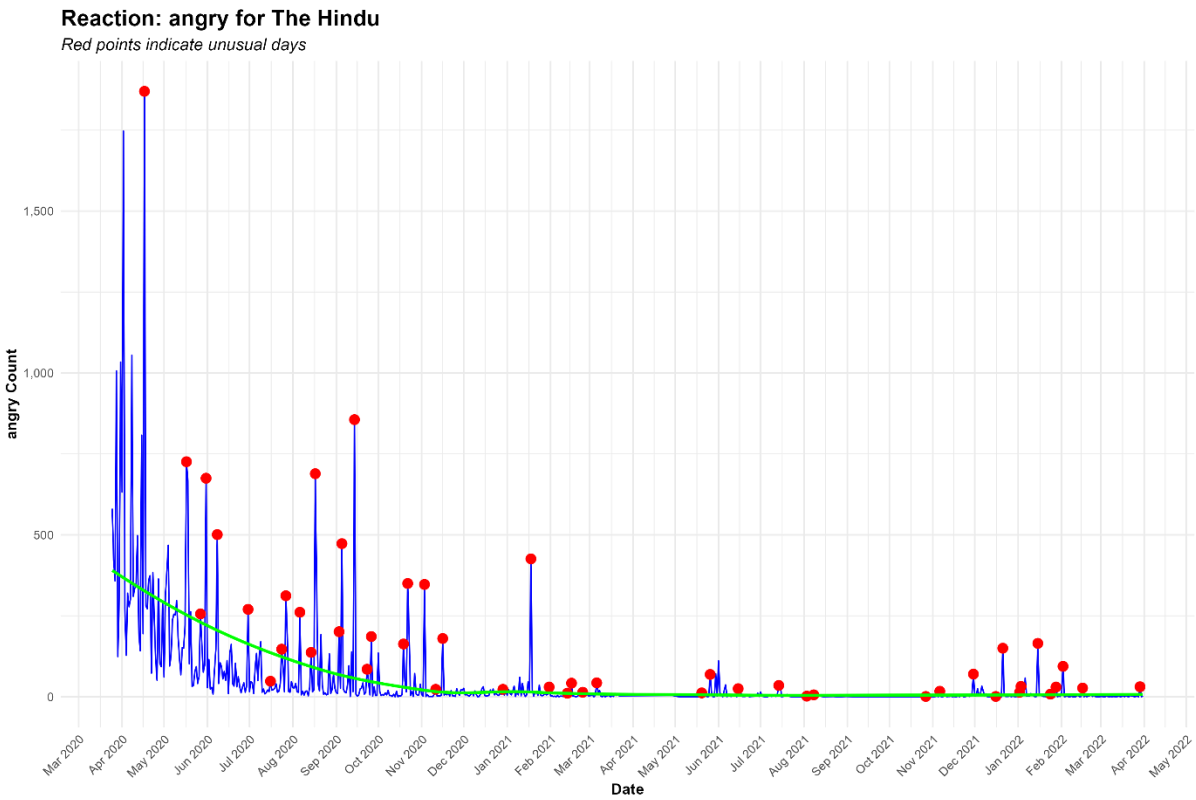


Figure 2 - *Unusual days for Indian Express with all Reactions*


Reaction: angry for The Hindu
Red points indicate unusual days
angry Count
1,500
1,000
500
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
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Sep 2021
Oct 2021
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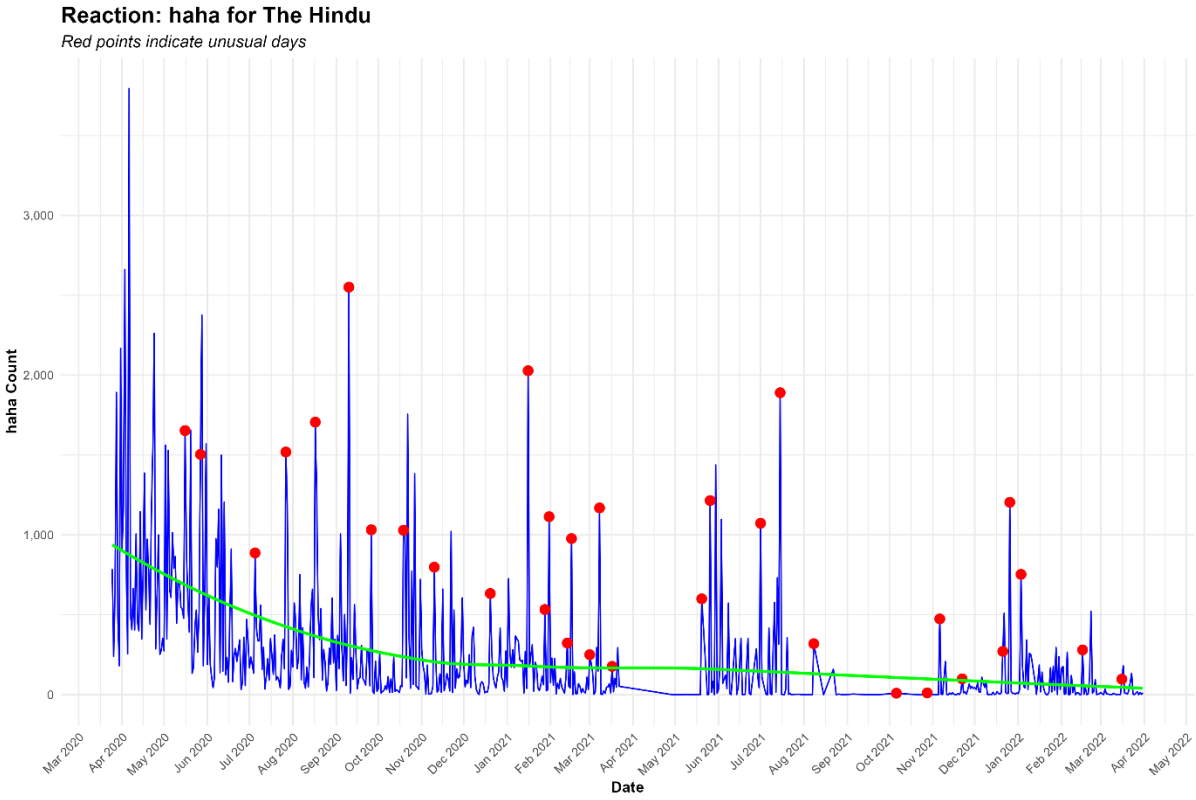
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: haha for The Hindu
Red points indicate unusual days
haha Count
3,000
2,000
1,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
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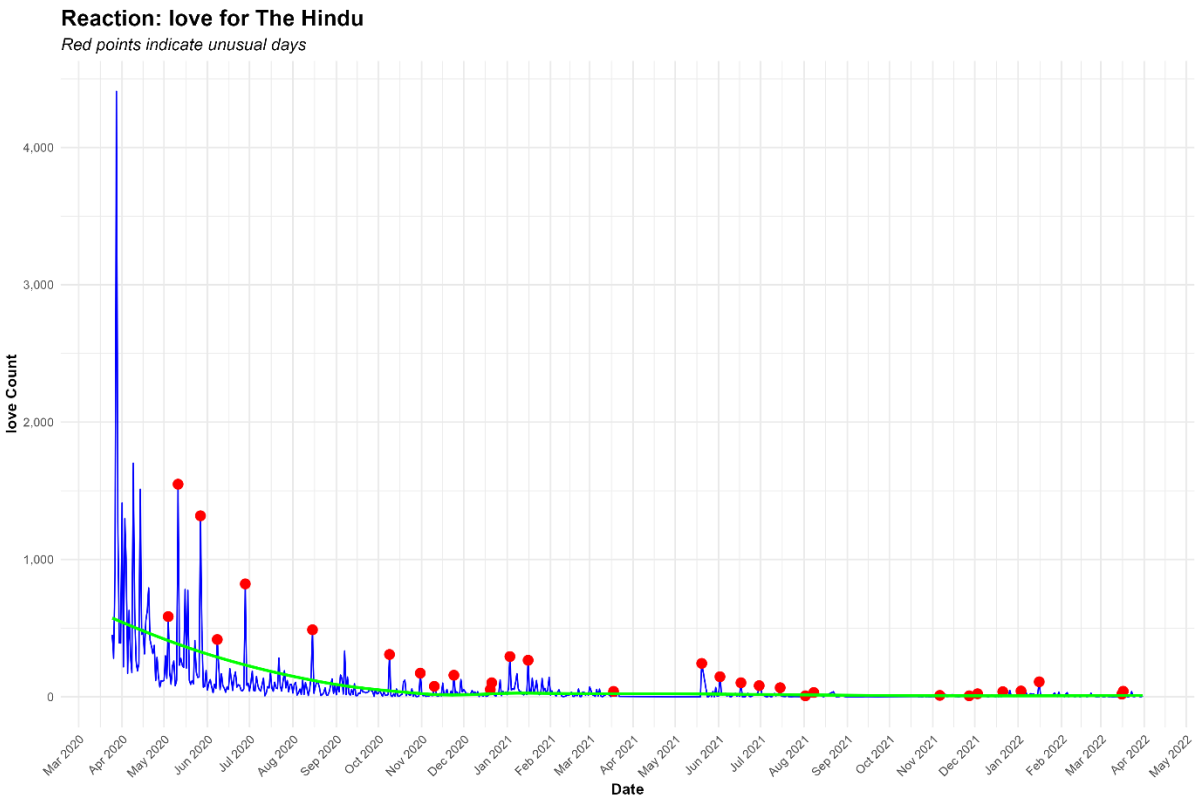
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: love for The Hindu
Red points indicate unusual days
love Count
4,000
3,000
2,000
1,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
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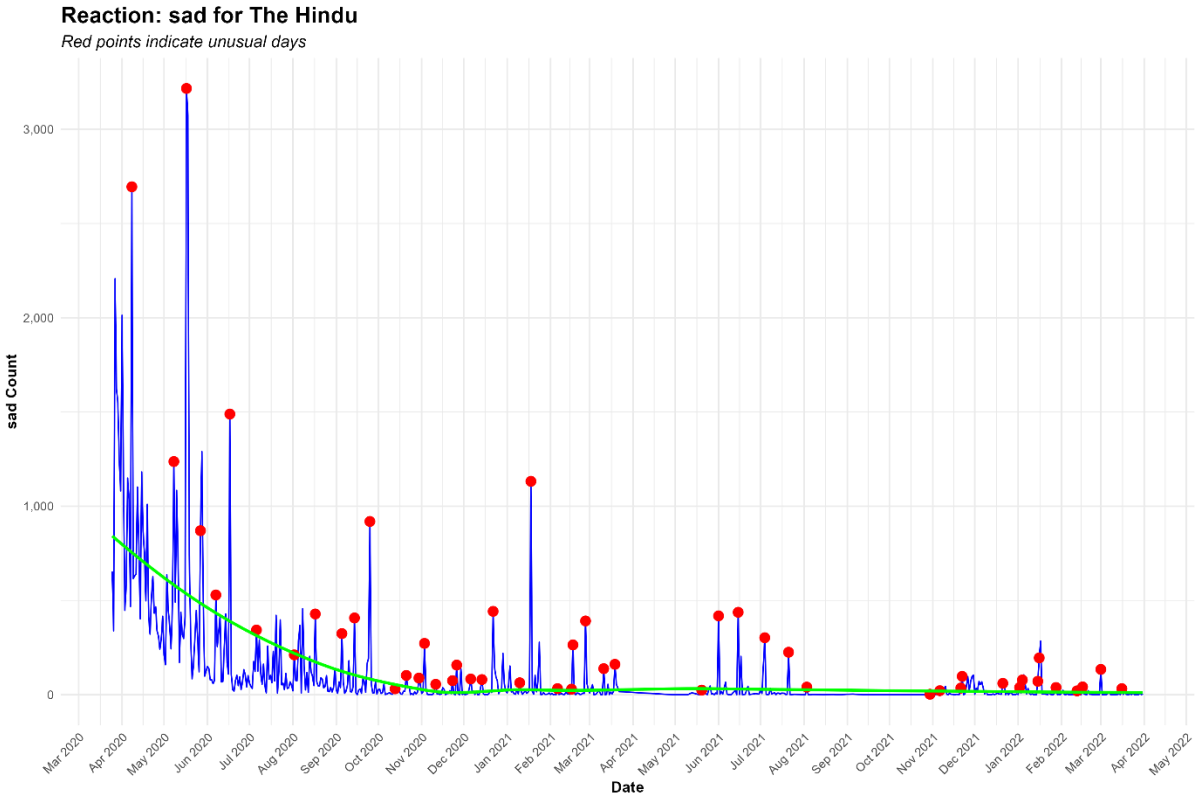
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: sad for The Hindu
Red points indicate unusual days
sad Count
3,000
2,000
1,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date

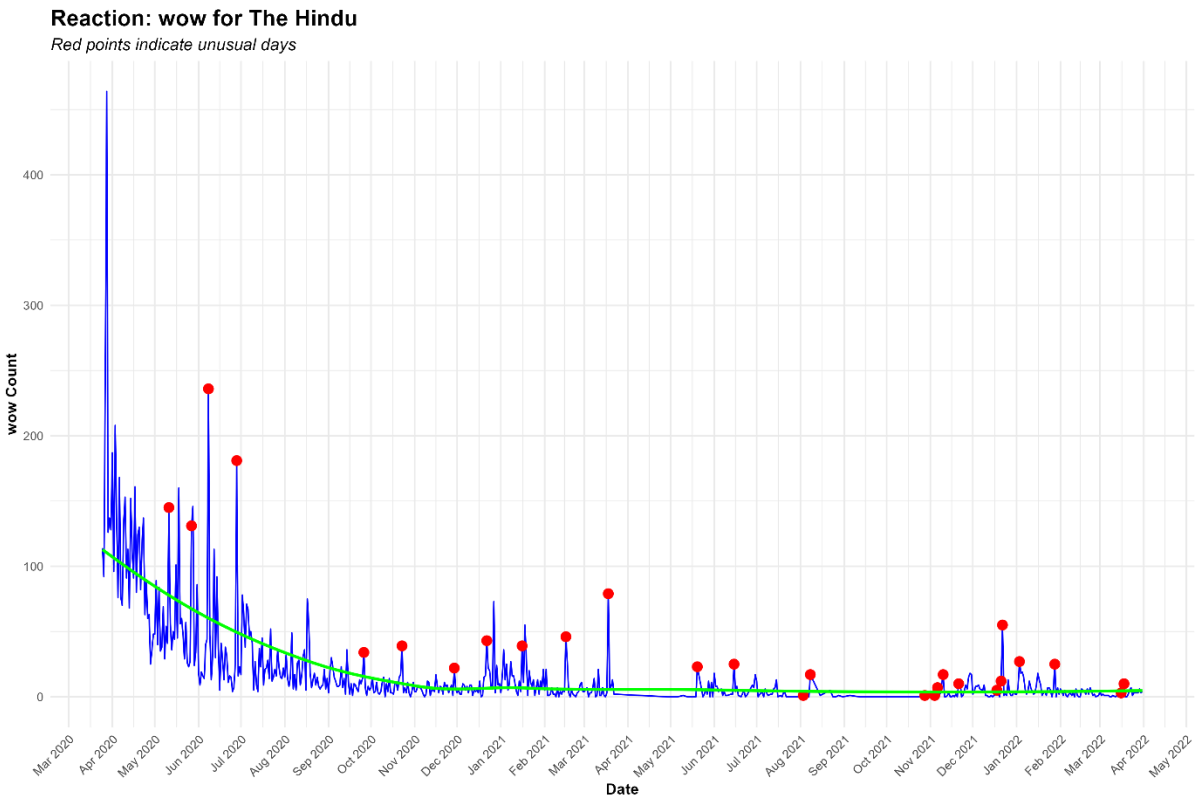
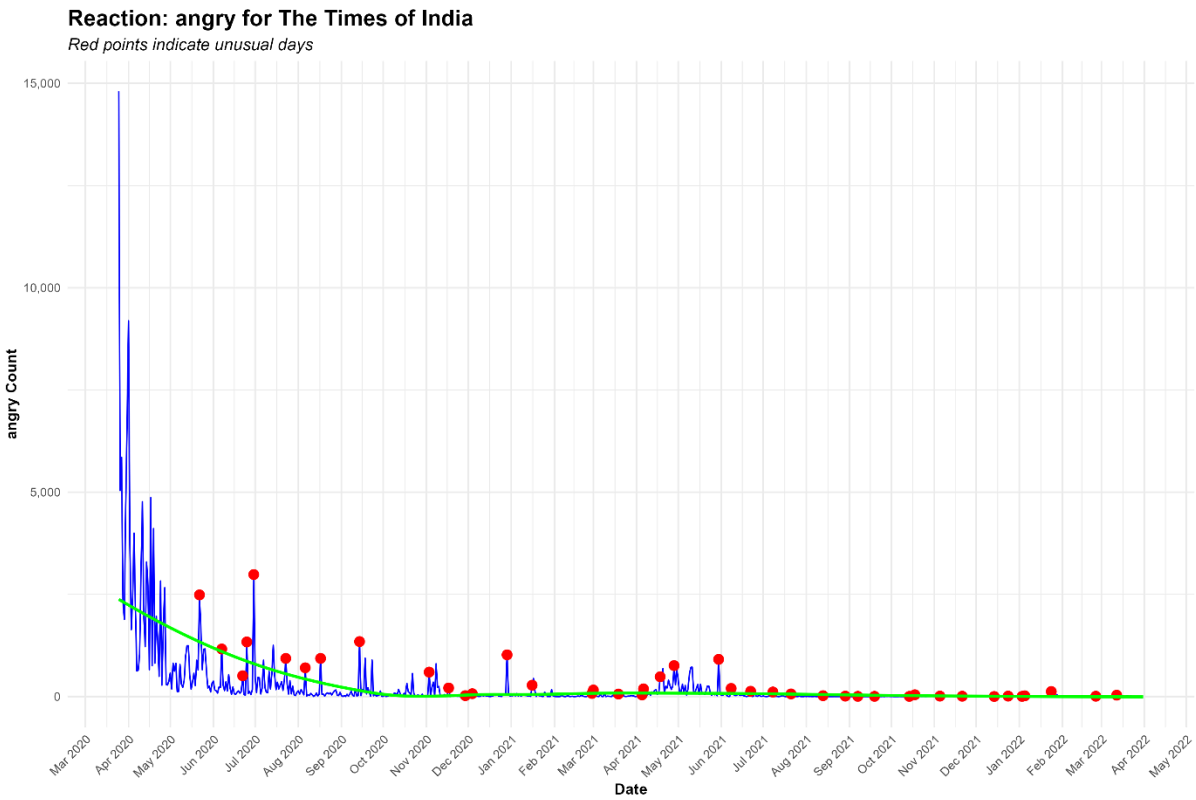
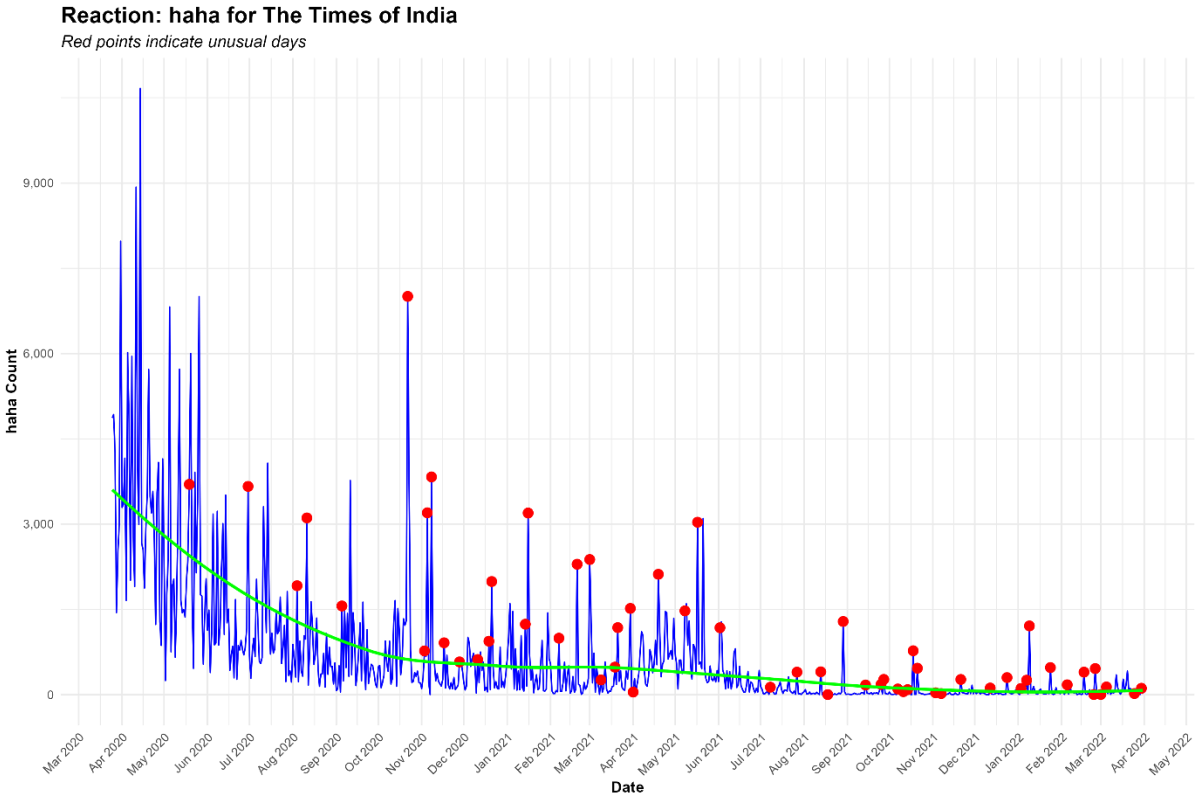


Figure 3 - *Unusual days for The Hindu with all Reactions*


Reaction: angry for The Times of India
Red points indicate unusual days
angry Count
15,000
10,000
5,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: haha for The Times of India
Red points indicate unusual days
haha Count
9,000
6,000
3,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
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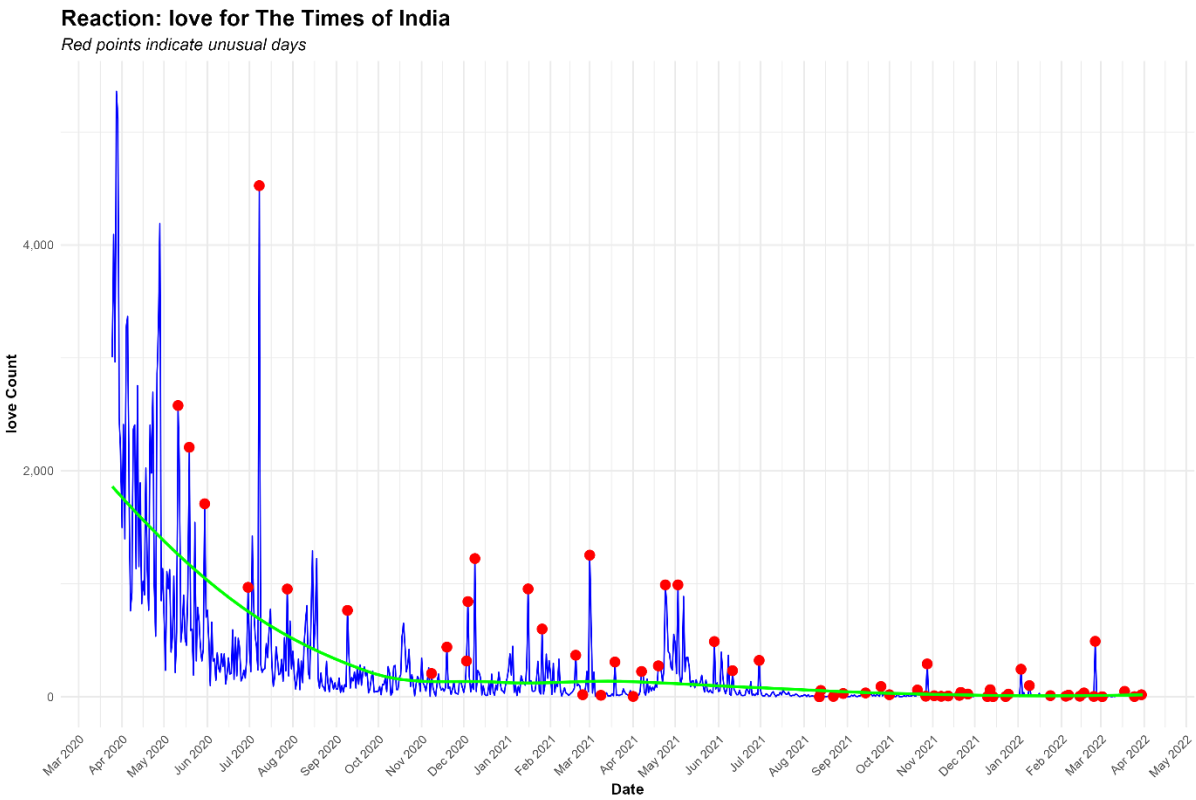
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: love for The Times of India
Red points indicate unusual days
love Count
4,000
2,000
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
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Aug 2021
Sep 2021
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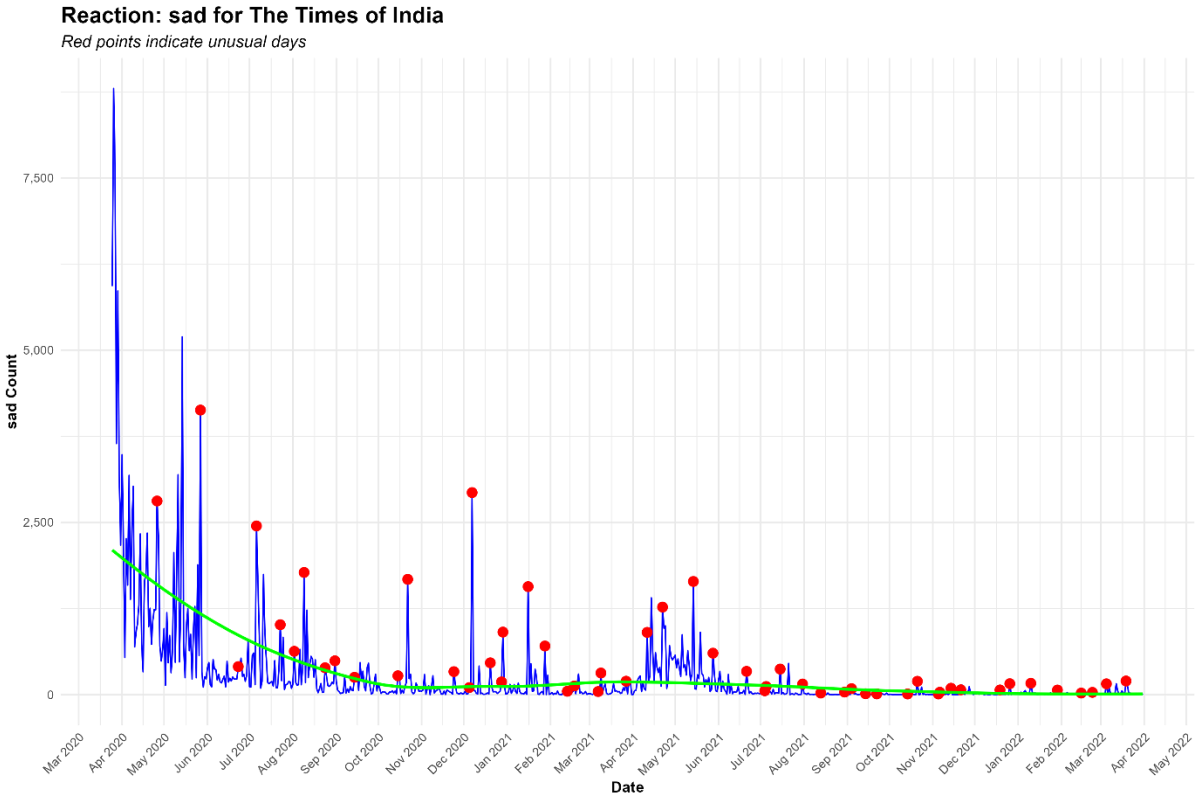
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022
Apr 2022
May 2022
Date


Reaction: sad for The Times of India
Red points indicate unusual days
sad Count
7,500
5,000
2,500
0
Mar 2020
Apr 2020
May 2020
Jun 2020
Jul 2020
Aug 2020
Sep 2020
Oct 2020
Nov 2020
Dec 2020
Jan 2021
Feb 2021
Mar 2021
Apr 2021
May 2021
Jun 2021
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Aug 2021
Sep 2021
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Nov 2021
Dec 2021
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Feb 2022
Mar 2022
Apr 2022
May 2022
Date

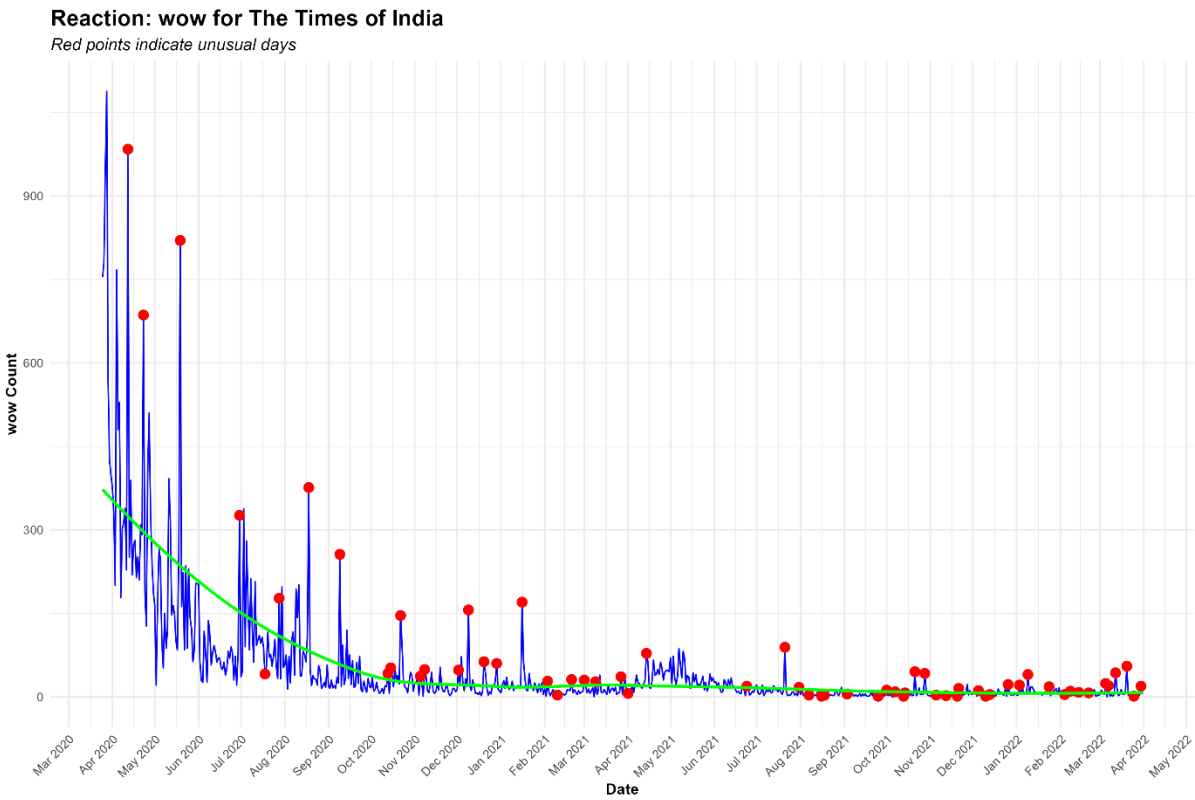


Figure 4 - *Unusual days for The Times of India with all Reactions*

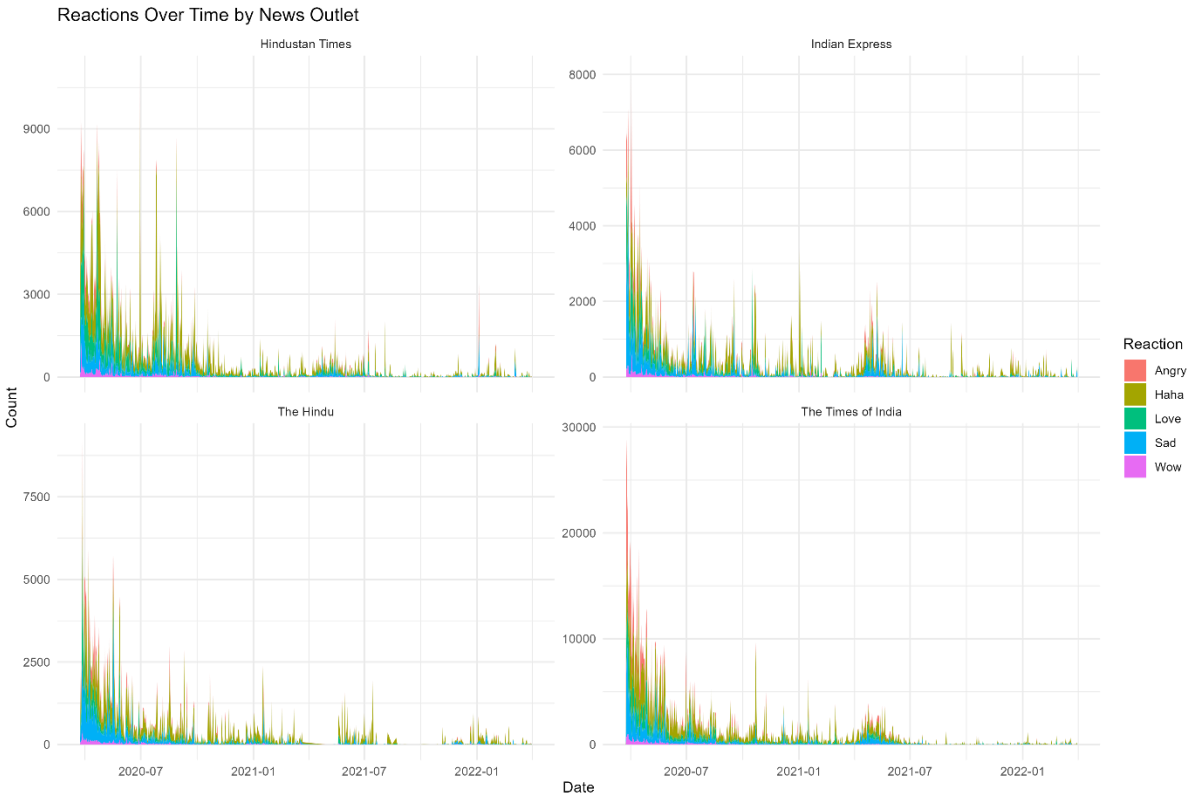


Figure 5 - *Reactions over Time by each News outlets*

	Hindustan Times	Indian Express	The Hindu	The Times of India
Hindustan Times	1	0.611362067	0.681791918	0.751238548
Indian Express	0.611362067	1	0.689957522	0.766722483
The Hindu	0.681791918	0.689957522	1	0.7965852
The Times of India	0.751238548	0.766722483	0.7965852	1

Table 1 - *Correlation across outlets*

	Love	Haha	Wow	Angry	Sad
Love	1	0.454278	0.685591	0.528077	0.540999
Haha	0.454278	1	0.503079	0.520665	0.473881
Wow	0.685591	0.503079	1	0.591332	0.589141
Angry	0.528077	0.520665	0.591332	1	0.642839
Sad	0.540999	0.473881	0.589141	0.642839	1

Table 2 - *Correlation within outlet Hindustan Times*

	Love	Haha	Wow	Angry	Sad
Love	1	0.385291	0.77708	0.468811	0.510981
Haha	0.385291	1	0.440309	0.364401	0.312192
Wow	0.77708	0.440309	1	0.450192	0.539188
Angry	0.468811	0.364401	0.450192	1	0.562458
Sad	0.510981	0.312192	0.539188	0.562458	1

Table 3 - *Correlation within outlet Indian Express*

	Love	Haha	Wow	Angry	Sad
Love	1	0.467989	0.842236	0.45194	0.504379
Haha	0.467989	1	0.586027	0.506774	0.384813
Wow	0.842236	0.586027	1	0.649364	0.626187
Angry	0.45194	0.506774	0.649364	1	0.646133
Sad	0.504379	0.384813	0.626187	0.646133	1

Table 4 - *Correlation within outlet The Hindu*

	Love	Haha	Wow	Angry	Sad
Love	1	0.601544	0.880168	0.587197	0.69864
Haha	0.601544	1	0.661818	0.583646	0.559839
Wow	0.880168	0.661818	1	0.665822	0.747737
Angry	0.587197	0.583646	0.665822	1	0.690716
Sad	0.69864	0.559839	0.747737	0.690716	1

Table 5 - *Correlation within outlet The Times of India*

account.name	month	Love	Haha	Wow	Angry	Sad	Total_Interactions
Hindustan Times	01-04-20	34937	54233	5225	13083	20888	1172104
Hindustan Times	01-05-20	28414	28458	3518	5479	11320	848786
Hindustan Times	01-08-20	18955	28096	2032	2569	9930	510554
Hindustan Times	01-03-20	16853	13767	3050	8080	11364	468057
Hindustan Times	01-07-20	11336	25535	1670	3137	6861	399050
Indian Express	01-04-20	18581	26054	3696	12656	19757	493936
Indian Express	01-05-20	9188	13524	1609	4018	8852	235372
Indian Express	01-07-20	4307	6994	1047	3960	8871	197627
Indian Express	01-03-20	6577	4691	1198	5137	13916	195651
Indian Express	01-08-20	4257	6176	608	870	4130	140013
The Hindu	01-04-20	15254	27551	3149	12442	22442	549664
The Hindu	01-05-20	9797	24518	1909	6759	19318	366830
The Hindu	01-03-20	8135	6441	1304	3834	8698	220956
The Hindu	01-07-20	2749	9441	940	1842	3778	192784
The Hindu	01-06-20	3794	11768	1215	2481	5636	181689
The Times of India	01-04-20	54726	109811	10393	65792	46498	1479192
The Times of India	01-05-20	25914	75953	5641	20549	33969	831943
The Times of India	01-03-20	25184	29120	4962	41316	37273	732464
The Times of India	01-07-20	16795	35082	3377	10317	14742	630329
The Times of India	01-08-20	9956	23315	2248	3606	10419	419794

Table 6 - *Total Interactions monthly spikes*

account.name	week	Love	Haha	Wow	Angry	Sad	Total_Interactions
Hindustan Times	29-03-20	11977	8534	1335	5263	8580	400306
Hindustan Times	19-04-20	15219	18728	2286	3307	7389	391845
Hindustan Times	22-03-20	9673	9348	2312	5575	5695	263141
Hindustan Times	12-04-20	5839	13657	908	3547	3827	248319
Hindustan Times	05-04-20	5732	10367	960	2175	4336	217114
Indian Express	29-03-20	6957	6703	1275	6685	6138	163728
Indian Express	22-03-20	5465	2411	999	3565	11429	151929
Indian Express	05-04-20	3517	5340	760	3638	5269	128736
Indian Express	12-04-20	4572	8531	641	2531	5443	119169
Indian Express	26-04-20	2819	7433	765	1019	3603	86439
The Hindu	29-03-20	5940	8438	1020	4255	8079	176402
The Hindu	22-03-20	6072	3577	913	2369	4824	149337
The Hindu	12-04-20	3745	5005	774	3985	5561	145161
The Hindu	05-04-20	3895	7025	769	2934	7270	144633
The Hindu	19-04-20	3004	7443	743	1827	3804	110235
The Times of India	29-03-20	18682	25885	3061	30249	19699	496306
The Times of India	22-03-20	15441	15520	3575	28041	26021	475356
The Times of India	05-04-20	12405	32359	2362	16224	13113	391833
The Times of India	12-04-20	10578	27716	2612	15458	9108	344964
The Times of India	19-04-20	10495	23524	2068	11853	8867	294936

Table 7 - *Total Interactions weekly spikes*

account.name	TopReactic	postUrl	PostDateTi	Like	Love	Wow	Haha	Sad	Angry	Care
Hindustan Times	Angry	https://ww	2022-01-0	7364	51	110	146	1460	1707	32
Hindustan Times	Care	https://ww	2020-08-2	29477	6244	264	34	9	3	483
Hindustan Times	Haha	https://ww	2020-07-2	3893	201	31	4311	14	73	15
Hindustan Times	Like	https://ww	2020-05-0	70689	1543	183	930	20	25	140
Hindustan Times	Love	https://ww	2020-08-2	29477	6244	264	34	9	3	483
Hindustan Times	Sad	https://ww	2020-03-2	1853	10	45	9	1527	13	0
Hindustan Times	Wow	https://ww	2020-03-2	5207	39	1045	67	184	12	0

Table 8- *Hindustan Times top reaction posts*

account.name	TopReaction	postUrl	PostDateTin	Like	Love	Wow	Haha	Sad	Angry	Care
Indian Express	Angry	https://ww	2020-07-13	5115	174	38	46	112	1465	19
Indian Express	Care	https://ww	2020-06-01	7166	849	45	7	0	2	253
Indian Express	Haha	https://ww	2021-01-02	2315	116	20	3410	6	19	9
Indian Express	Like	https://ww	2020-07-10	19931	217	19	8	5	2	32
Indian Express	Love	https://ww	2020-10-16	8213	2227	306	14	13	6	95
Indian Express	Sad	https://ww	2020-03-28	2089	14	77	20	1743	679	0
Indian Express	Wow	https://ww	2020-04-03	4251	556	519	12	1	0	0

Table 9 - *Indian Express top reaction posts*

account.na	TopReaction	postUrl	PostDateTin	Like	Love	Wow	Haha	Sad	Angry	Care
The Hindu	Angry	https://ww	2020-04-02	1110	8	27	117	298	1077	0
The Hindu	Care	https://ww	2020-05-11	6862	1283	87	44	134	6	561
The Hindu	Haha	https://ww	2020-04-06	1670	73	30	2913	15	25	0
The Hindu	Like	https://ww	2020-03-28	25337	2216	190	34	4	2	0
The Hindu	Love	https://ww	2020-03-28	25337	2216	190	34	4	2	0
The Hindu	Sad	https://ww	2020-05-17	2429	11	12	5	3021	207	22
The Hindu	Wow	https://ww	2020-03-28	25337	2216	190	34	4	2	0

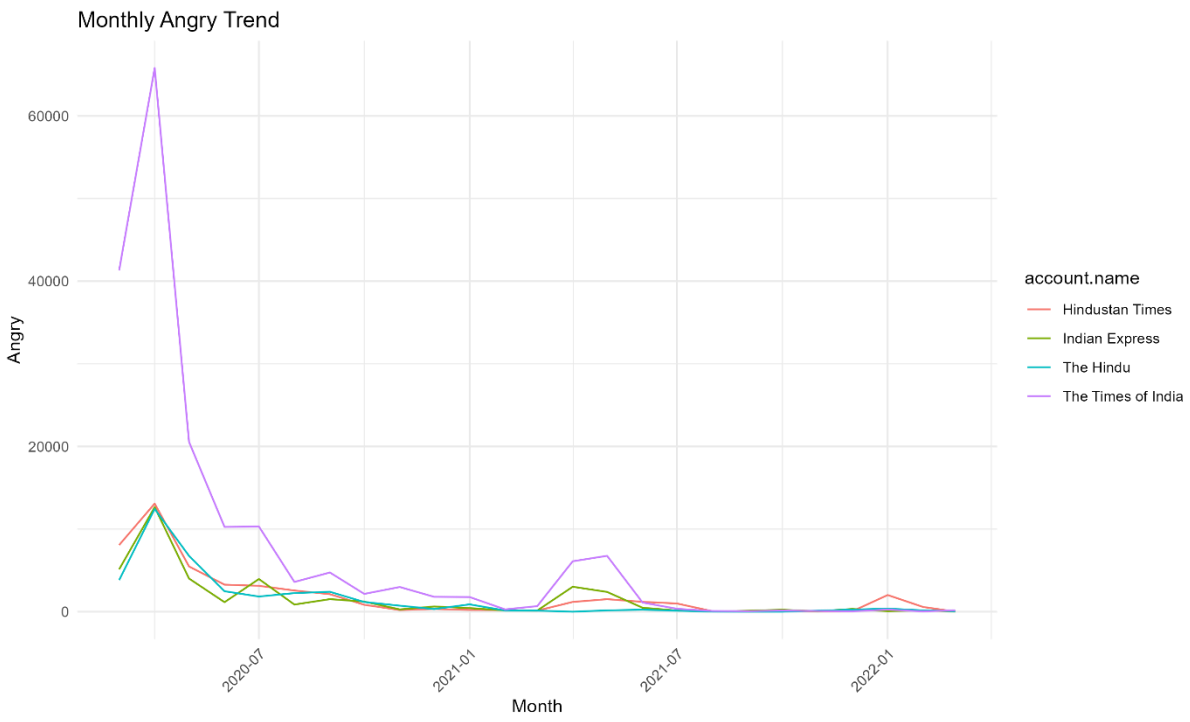
Table 10 - *The Hindu top reaction posts*

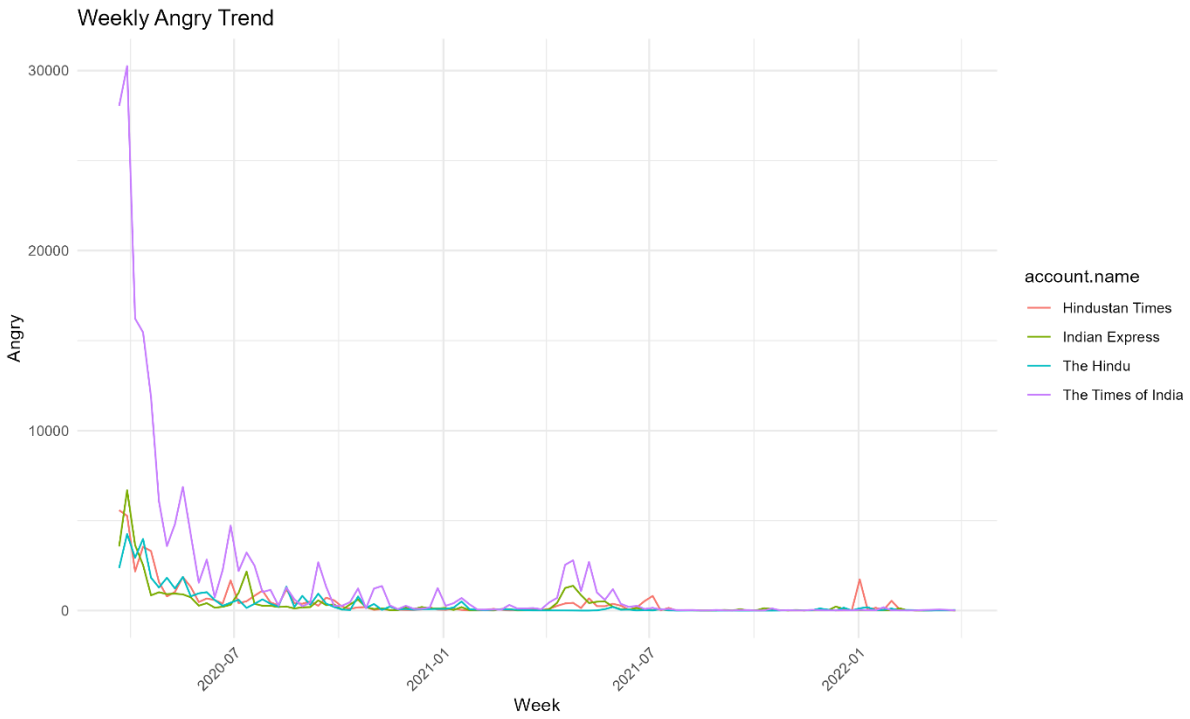
account.name	TopReaction	postUrl	PostDateTin	Like	Love	Wow	Haha	Sad	Angry	Care
The Times of India	Angry	https://ww	2020-03-25	4002	49	44	184	593	4833	0
The Times of India	Care	https://ww	2020-07-08	52006	4259	86	117	242	31	693
The Times of India	Haha	https://ww	2020-10-22	3742	77	45	5624	52	453	7
The Times of India	Like	https://ww	2020-07-08	52006	4259	86	117	242	31	693
The Times of India	Love	https://ww	2020-07-08	52006	4259	86	117	242	31	693
The Times of India	Sad	https://ww	2020-03-26	5243	41	15	11	4583	107	0
The Times of India	Wow	https://ww	2020-04-12	8235	1036	682	46	1	0	0

Table 11 - *The Times of India top reaction posts*

```
account.name            date                  Love           Haha              Wow
Length:2761        Min.   :2020-03-24   Min.   :   0   Min.   :    0.0   Min.   :   0.00
Class :character   1st Qu.:2020-09-12   1st Qu.:   5   1st Qu.:   15.0   1st Qu.:   2.00
Mode  :character   Median :2021-03-05   Median :  25   Median :  100.0   Median :   7.00
                   Mean   :2021-03-18   Mean   : 167   Mean   :  384.5   Mean   :  30.52
                   3rd Qu.:2021-09-23   3rd Qu.: 121   3rd Qu.:  404.0   3rd Qu.:  23.00
                   Max.   :2022-03-31   Max.   :6541   Max.   :10666.0   Max.   :1254.00
    Angry              Sad         Total Interactions
Min.   :    0.0   Min.   :   0.0   Min.   :     3
1st Qu.:    1.0   1st Qu.:   2.0   1st Qu.:   423
Median :    7.0   Median :  18.0   Median :  1640
Mean   :  110.6   Mean   : 166.6   Mean   :  5783
3rd Qu.:   49.0   3rd Qu.: 117.0   3rd Qu.:  5870
Max.   :14632.0   Max.   :8804.0   Max.   :136493
```

Table 12 - *Summary Statistics*


Monthly Angry Trend
60000
40000
20000
0
Angry
2020-07
2021-01
2021-07
2022-01
Month
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India


Weekly Angry Trend
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20000
10000
0
Angry
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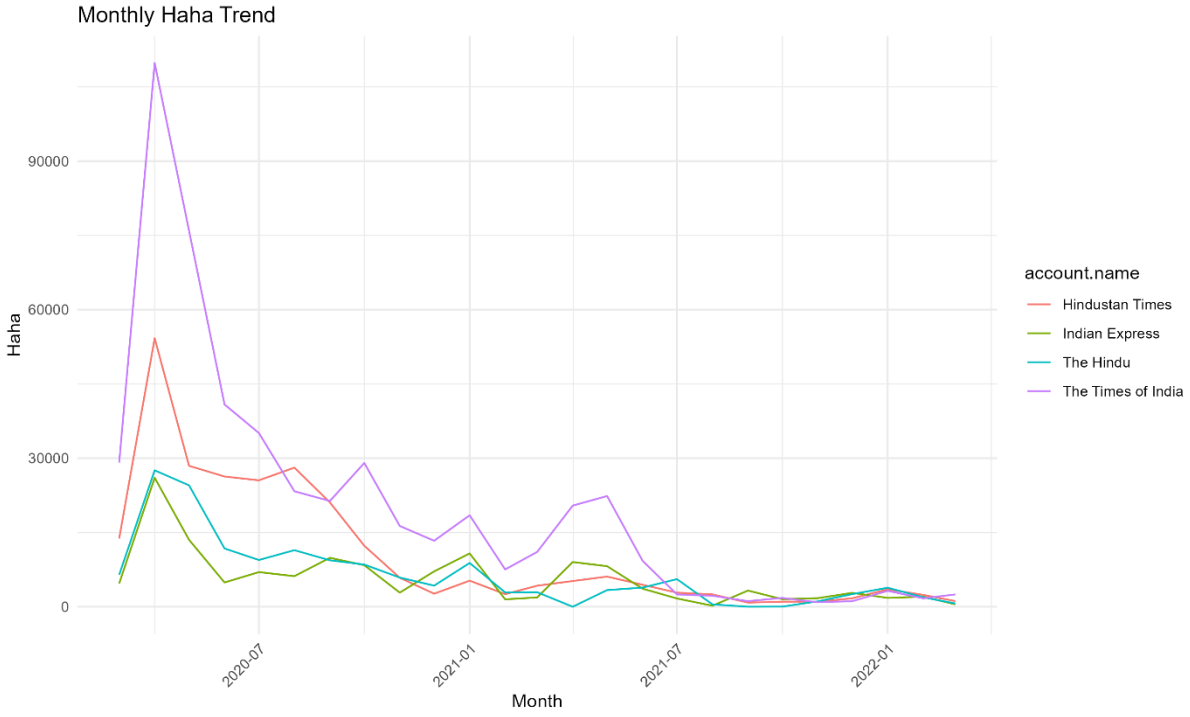
2021-01
2021-07
2022-01
Week
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India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Haha
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60000
30000
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2021-01
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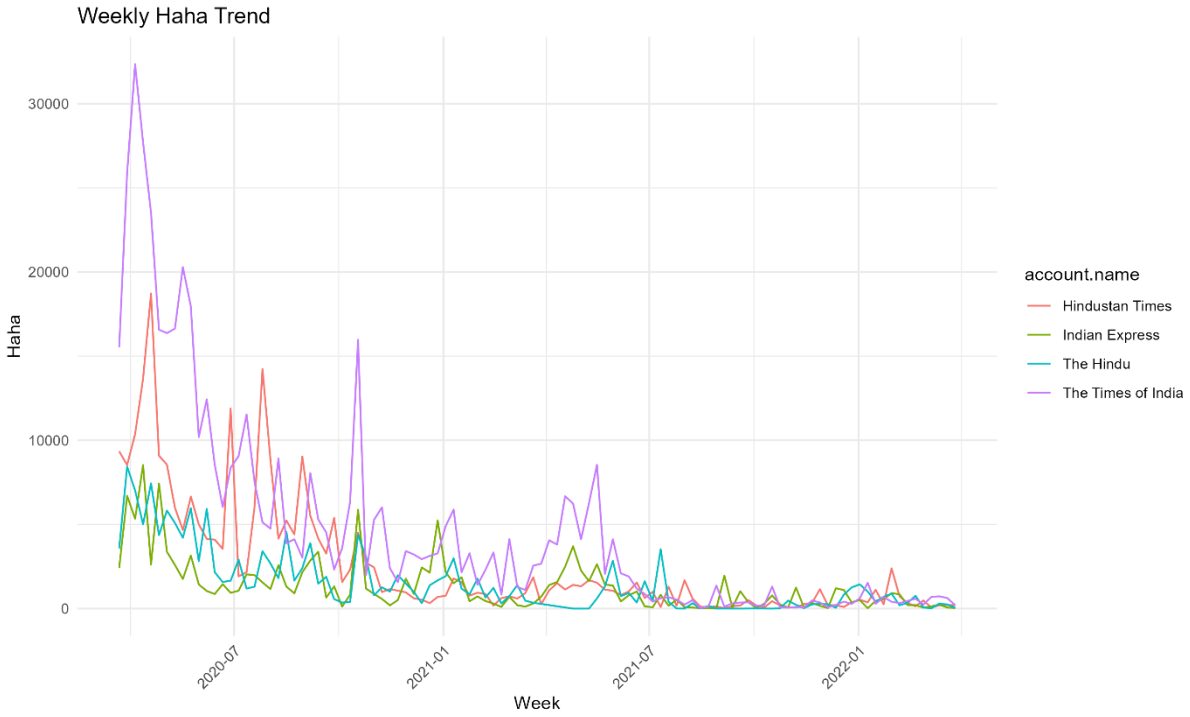
2022-01
Month
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India


Weekly Haha Trend
Haha
30000
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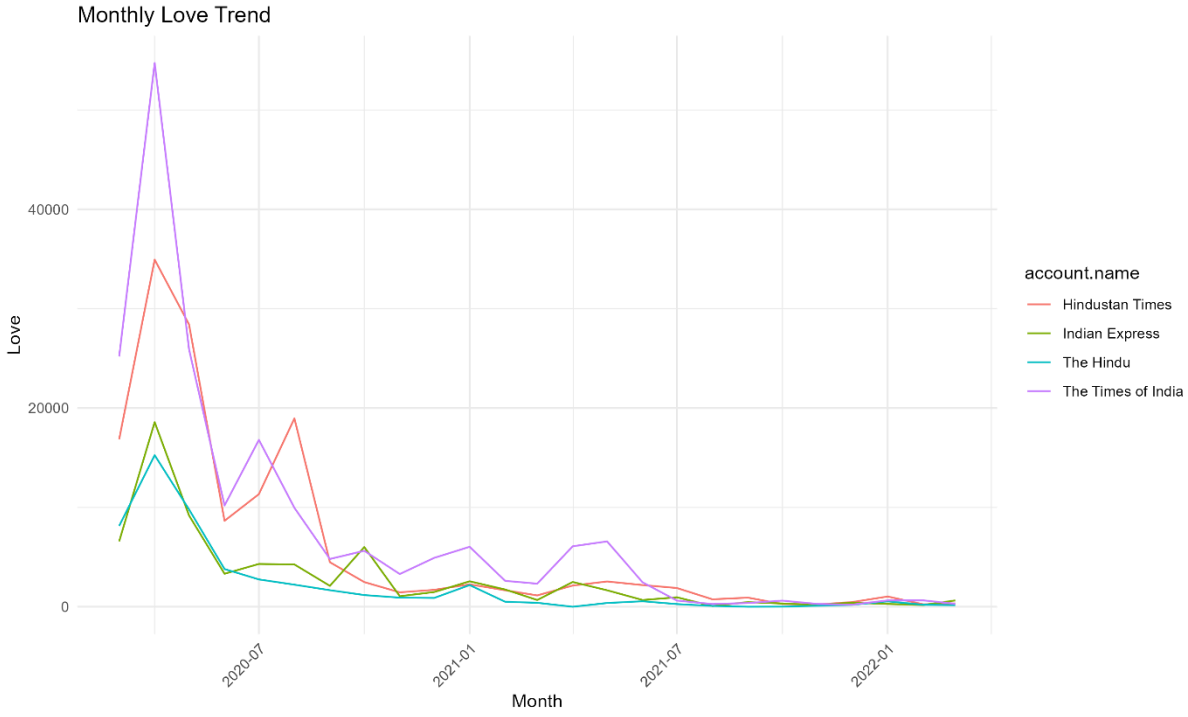
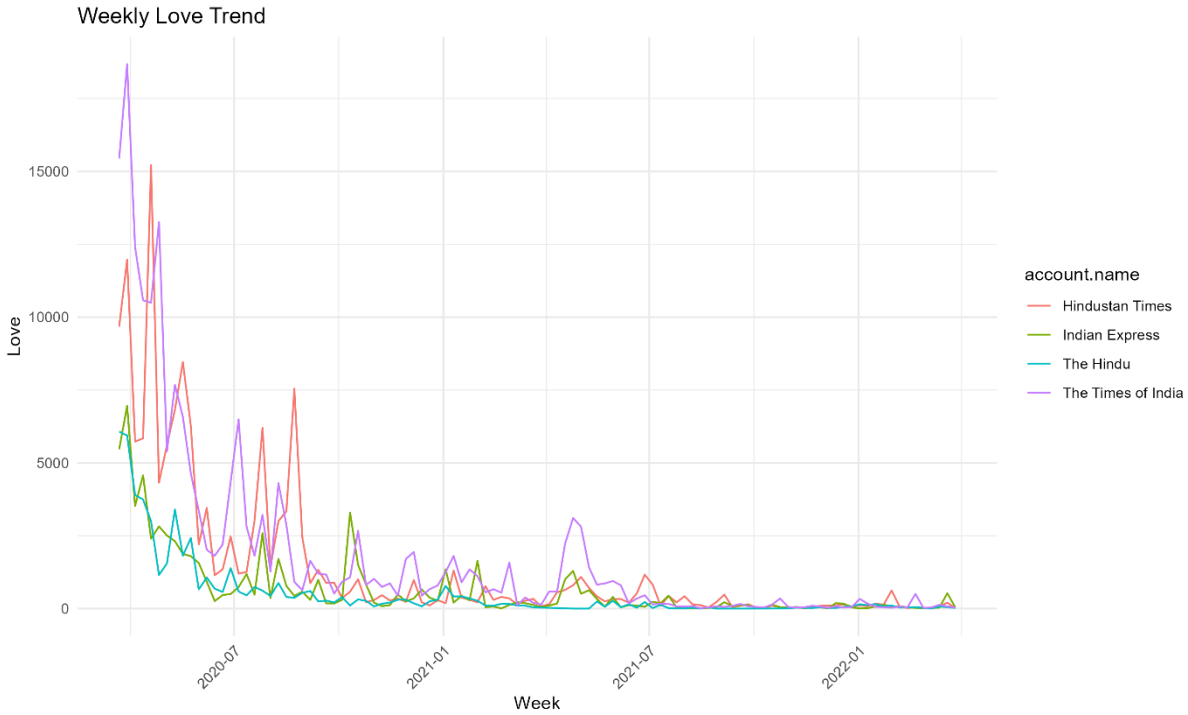
2020-07
2021-01
2021-07
2022-01
Week
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India


Monthly Love Trend
Love
40000
20000
0
2020-07
2021-01
2021-07
2022-01
Month
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India


Weekly Love Trend
Love
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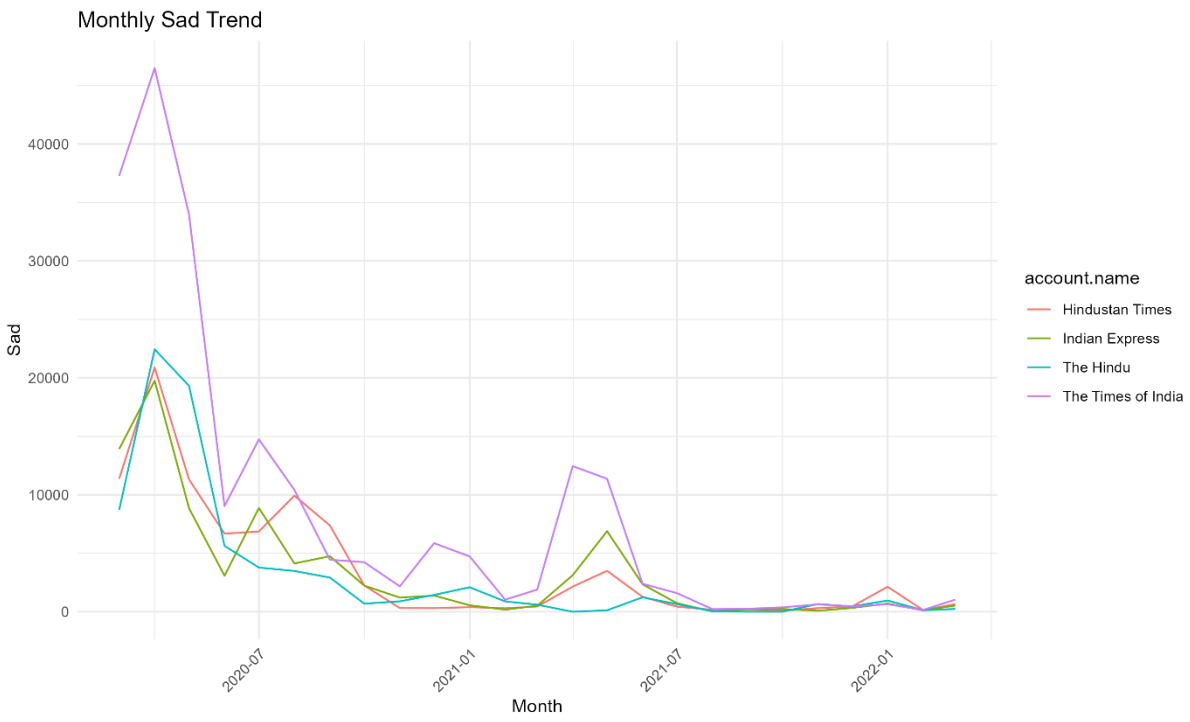
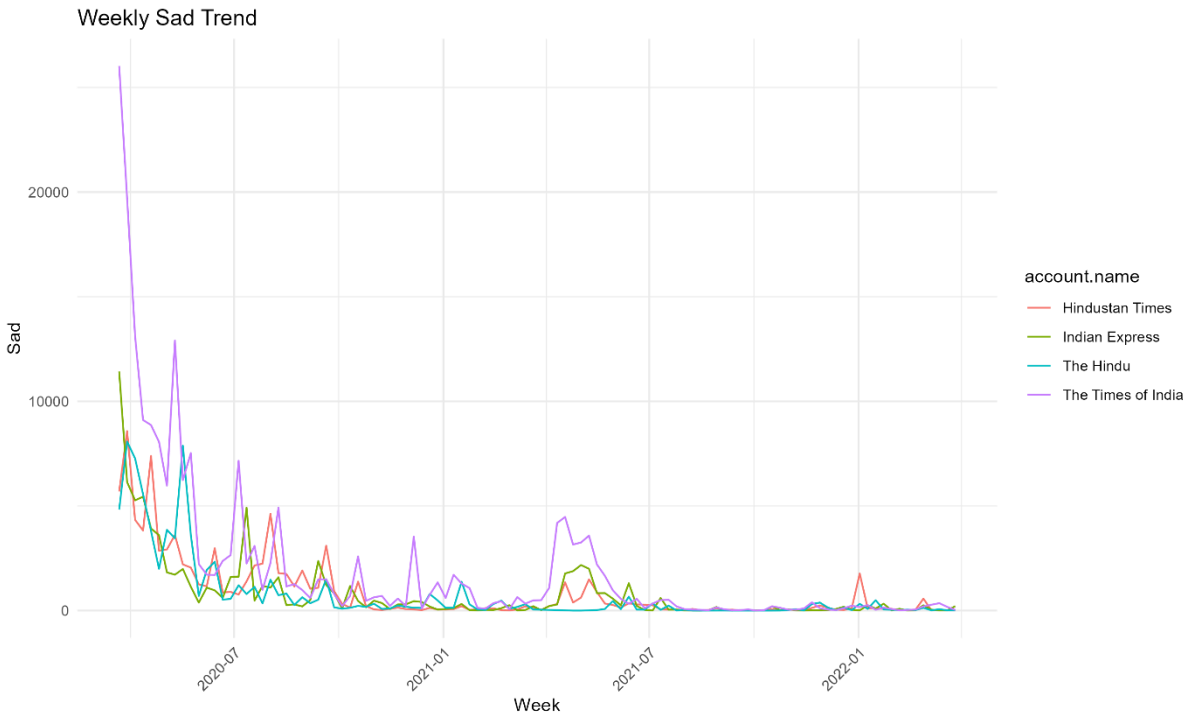
10000
5000
0
2020-07
2021-01
2021-07
2022-01
Week
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India


Monthly Sad Trend
Sad
40000
30000
20000
10000
0
2020-07
2021-01
2021-07
2022-01
Month
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India


Weekly Sad Trend
Sad
20000
10000
0
2020-07
2021-01
2021-07
2022-01
Week
account.name
Hindustan Times
Indian Express
The Hindu
The Times of India

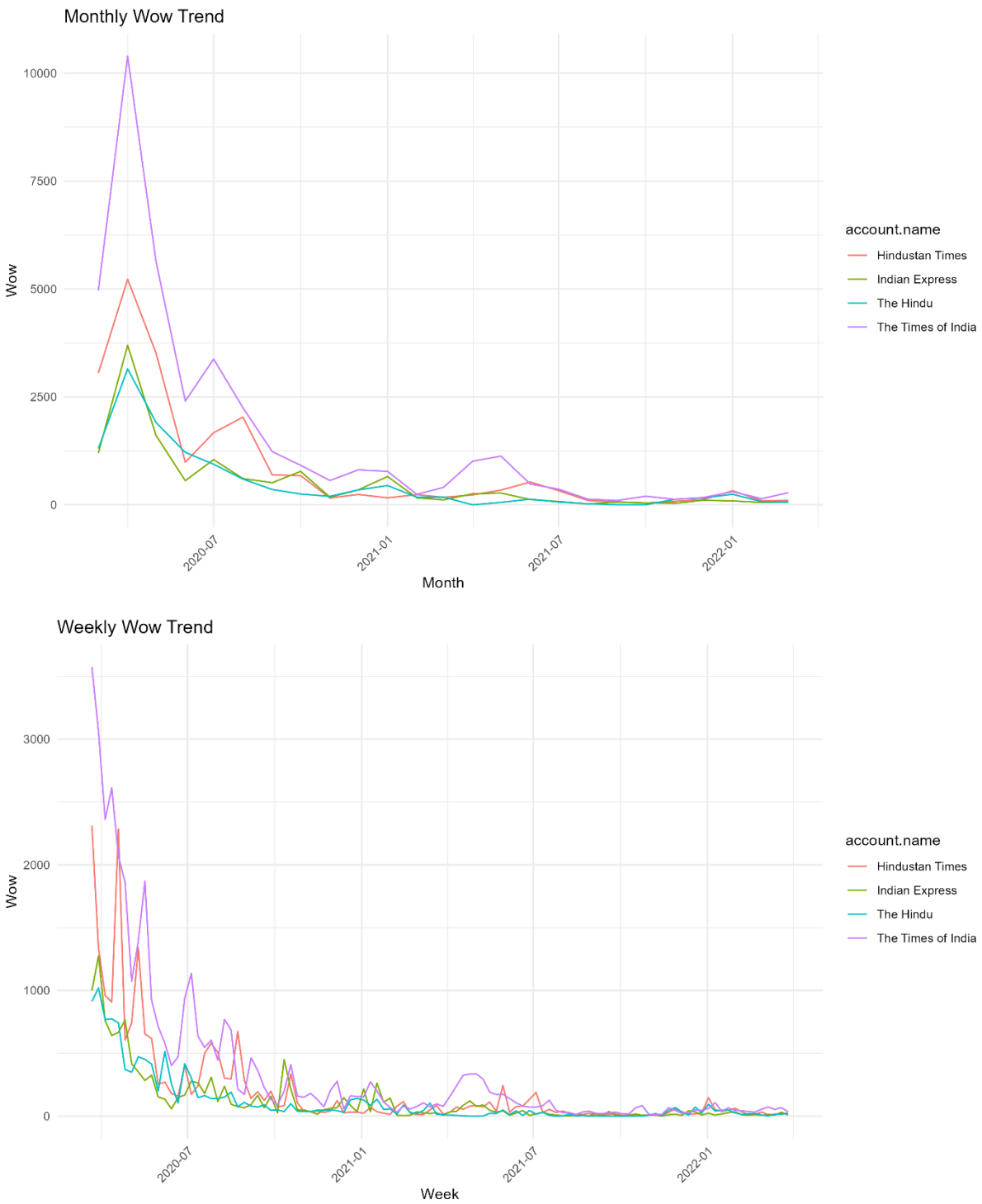


Figure 6 - *Reactions monthly and weekly trend*

Appendix C. Text Embedding Generation Using OpenAI API

This R code is for generating text embeddings using OpenAI's API. The code processes textual data and creates high-dimensional vector representations (embeddings) using the text embedding-3-large model.

```
# Load necessary libraries
suppressPackageStartupMessages({
  library(dplyr)
  library(readr)
  library(stringr)
  library(openai)
  library(logger)
  library(tidyr)
})

# Configuration
config <- list(
  retry_attempts = 3,
  sleep_time = 0.5,
  batch_size = 100,
  embedding_dim = 3072,
  model = "text-embedding-3-large",
  rate_limit_per_minute = 150  # OpenAI rate limit
)
```

```
# Set up logging
log_dir <- "./logs"
if (!dir.exists(log_dir)) dir.create(log_dir)
log_appender(appender_file(file.path(log_dir,                    format(Sys.time(),
"log_%Y%m%d_%H%M%S.log"))))

# Initialize rate limiting
last_call_time <- Sys.time()
call_times <- numeric()

# Rate limiting function
enforce_rate_limit <- function() {
  current_time <- Sys.time()
  # Remove calls older than 1 minute
  call_times <<- call_times[call_times > (current_time - 60)]
  # If near rate limit, wait
  if (length(call_times) >= config$rate_limit_per_minute) {
    wait_time <- 60 - as.numeric(difftime(current_time, min(call_times), units =
"secs"))
    if (wait_time > 0) {
      log_info(sprintf("Rate limit approaching, waiting %.2f seconds",
wait_time))
      Sys.sleep(wait_time)
    }
  }
```

```
  # Record this call
  call_times <<- c(call_times, current_time)
}

# Function to get embedding with retry logic
get_embeddings <- function(text, config) {
  enforce_rate_limit()

  for (attempt in 1:config$retry_attempts) {
    result <- tryCatch({
      openai::create_embedding(
        model = config$model,
        input = text,
        openai_organization = Sys.getenv("OPENAI_UNIURB_ORG_ID"),
        openai_api_key = Sys.getenv("OPENAI_VERA_PROJ_ID_API_KEY")
      )
    }, error = function(e) {
      log_error(sprintf("Attempt %d failed: %s", attempt, e$message))
      if (attempt == config$retry_attempts) {
        log_error("All retry attempts exhausted")
        return(NULL)
      }
      Sys.sleep(attempt * config$sleep_time)  # Exponential backoff
      NULL
```

```
    })

    if (!is.null(result) && !is.null(result$data$embedding)) {
      log_info(sprintf("Successfully got embedding for text: %s...", substr(text, 1,
30)))
      return(result$data$embedding)
    }
  }

  return(rep(NA_real_, config$embedding_dim))
}

# Function to process texts in batches
process_batch <- function(texts, config) {
  embeddings <- vector("list", length(texts))

  for (i in seq_along(texts)) {
    if (is.na(texts[i]) || nchar(texts[i]) == 0) {
      log_warn(sprintf("Empty or NA text at index %d", i))
      embeddings[[i]] <- rep(NA_real_, config$embedding_dim)
      next
    }

    embeddings[[i]] <- get_embeddings(texts[i], config)
    Sys.sleep(config$sleep_time)
```

```
  }

  return(embeddings)
}

# Function to process a single RDS file
process_single_file <- function(file_path, config) {
  log_info(sprintf("Starting to process file: %s", file_path))

  # Create output directory if it doesn't exist
  output_dir <- "./processed_data"
  if (!dir.exists(output_dir)) {
    dir.create(output_dir)
    log_info("Created output directory")
  }

  # Load and validate data
  tryCatch({
    data <- readRDS(file_path)
    if (!"text_to_embed" %in% colnames(data)) {
      stop("File does not contain 'text_to_embed' column")
    }
  }, error = function(e) {
    log_error(sprintf("Error loading file: %s", e$message))
    stop(e)
```

```
})

# Remove duplicates and NA values
data <- data %>%
  distinct(text_to_embed, .keep_all = TRUE) %>%
  filter(!is.na(text_to_embed))

log_info(sprintf("Processing %d unique texts", nrow(data)))

# Process in batches
total_batches <- ceiling(nrow(data) / config$batch_size)
pb <- txtProgressBar(min = 0, max = total_batches, style = 3)

for (batch_idx in seq(1, nrow(data), by = config$batch_size)) {
  batch_end <- min(batch_idx + config$batch_size - 1, nrow(data))
  batch_texts <- data$text_to_embed[batch_idx:batch_end]

  # Process batch
  embeddings <- process_batch(batch_texts, config)
  data$text_embedding[batch_idx:batch_end] <- embeddings

  # Update progress bar
  setTxtProgressBar(pb, ceiling(batch_idx / config$batch_size))
}
 close(pb)
```

```
  # Save processed data
  output_file <- file.path(output_dir, basename(file_path))
  saveRDS(data, file = output_file)
  log_info(sprintf("Saved processed data to: %s", output_file))

  # Basic validation of results
  embedding_lengths <- sapply(data$text_embedding, length)
  na_count <- sum(is.na(embedding_lengths))

  log_info(sprintf("Processing complete. %d embeddings created, %d failed",
                   nrow(data) - na_count, na_count))

  return(data)
}

# Main execution
main <- function() {
  log_info("Starting embedding generation process")

  # Check for environment variables
  required_env_vars <- c("OPENAI_UNIURB_ORG_ID",
"OPENAI_VERA_PROJ_ID_API_KEY")
  missing_vars <- required_env_vars[!nzchar(Sys.getenv(required_env_vars))]
```

```
  if (length(missing_vars) > 0) {
    stop(sprintf("Missing required environment variables: %s",
                 paste(missing_vars, collapse = ", ")))
  }

  # Process file
  file_path <- "./data/sawood.rds"
  if (!file.exists(file_path)) {
    stop(sprintf("Input file not found: %s", file_path))
  }

  processed_data <- process_single_file(file_path, config)

  # Final summary
  log_info("Process completed successfully")
  return(processed_data)
}

# Run the main function
tryCatch({
  result <- main()
}, error = function(e) {
  log_error(sprintf("Process failed: %s", e$message))
  stop(e)
})
```

The code requires the following R packages:

```
library(dplyr)      # Data manipulation
library(readr)      # Data reading/writing
library(stringr)    # String manipulation
library(openai)     # OpenAI API interface
library(logger)     # Logging functionality
library(tidyr)      # Data tidying
```

Configuration Settings:

```
config <- list(
  retry_attempts = 3,            # Number of API retry attempts
  sleep_time = 0.5,              # Delay between API calls (seconds)
  batch_size = 100,              # Number of texts per batch
  embedding_dim = 3072,          # Embedding vector dimension
  model = "text-embedding-3-large",
  rate_limit_per_minute = 150   # API rate limit
)
```

Rate Limiting Implementation:

```
enforce_rate_limit <- function() {
  current_time <- Sys.time()
  call_times <<- call_times[call_times > (current_time - 60)]
```

```
  if (length(call_times) >= config$rate_limit_per_minute) {
    wait_time <- 60 - as.numeric(difftime(current_time, min(call_times), units =
"secs"))
    if (wait_time > 0) {
      log_info(sprintf("Rate limit approaching, waiting %.2f seconds",
wait_time))
      Sys.sleep(wait_time)
    }
  }
  call_times <<- c(call_times, current_time)
}
```

Embedding Generation:

```
get_embeddings <- function(text, config) {
  enforce_rate_limit()

  for (attempt in 1:config$retry_attempts) {
    result <- tryCatch({
      openai::create_embedding(
        model = config$model,
        input = text,
        openai_organization = Sys.getenv("OPENAI_UNIURB_ORG_ID"),
        openai_api_key = Sys.getenv("OPENAI_VERA_PROJ_ID_API_KEY")
      )
    }, error = function(e) {
```

```
      log_error(sprintf("Attempt %d failed: %s", attempt, e$message))
      if (attempt == config$retry_attempts) {
        log_error("All retry attempts exhausted")
        return(NULL)
      }
      Sys.sleep(attempt * config$sleep_time)
      NULL
    })

    if (!is.null(result) && !is.null(result$data$embedding)) {
      return(result$data$embedding)
    }
  }

  return(rep(NA_real_, config$embedding_dim))
}
```

Batch Processing:

```
process_batch <- function(texts, config) {
  embeddings <- vector("list", length(texts))

  for (i in seq_along(texts)) {
    if (is.na(texts[i]) || nchar(texts[i]) == 0) {
      log_warn(sprintf("Empty or NA text at index %d", i))
      embeddings[[i]] <- rep(NA_real_, config$embedding_dim)
```

```
      next
    }

    embeddings[[i]] <- get_embeddings(texts[i], config)
    Sys.sleep(config$sleep_time)
  }

  return(embeddings)
}
```

Main Processing Function:

```
process_single_file <- function(file_path, config) {
  log_info(sprintf("Starting to process file: %s", file_path))

  # Create output directory
  output_dir <- "./processed_data"
  if (!dir.exists(output_dir)) dir.create(output_dir)

  # Load and validate data
  data <- readRDS(file_path)
  if (!"text_to_embed" %in% colnames(data)) {
    stop("File does not contain 'text_to_embed' column")
```

```
  }

  # Remove duplicates and process
  data <- data %>%
    distinct(text_to_embed, .keep_all = TRUE) %>%
    filter(!is.na(text_to_embed))

  # Process in batches with progress bar
  total_batches <- ceiling(nrow(data) / config$batch_size)
  pb <- txtProgressBar(min = 0, max = total_batches, style = 3)

  for (batch_idx in seq(1, nrow(data), by = config$batch_size)) {
    batch_end <- min(batch_idx + config$batch_size - 1, nrow(data))
    batch_texts <- data$text_to_embed[batch_idx:batch_end]
    data$text_embedding[batch_idx:batch_end]  <-  process_batch(batch_texts,
config)
    setTxtProgressBar(pb, ceiling(batch_idx / config$batch_size))
  }

  close(pb)

  # Save results
  saveRDS(data, file = file.path(output_dir, basename(file_path)))
  return(data)
}
```

Set up environment variables:

Sys.setenv(OPENAI_UNIURB_ORG_ID="org-id")

Sys.setenv(OPENAI_VERA_PROJ_ID_API_KEY="api-key")

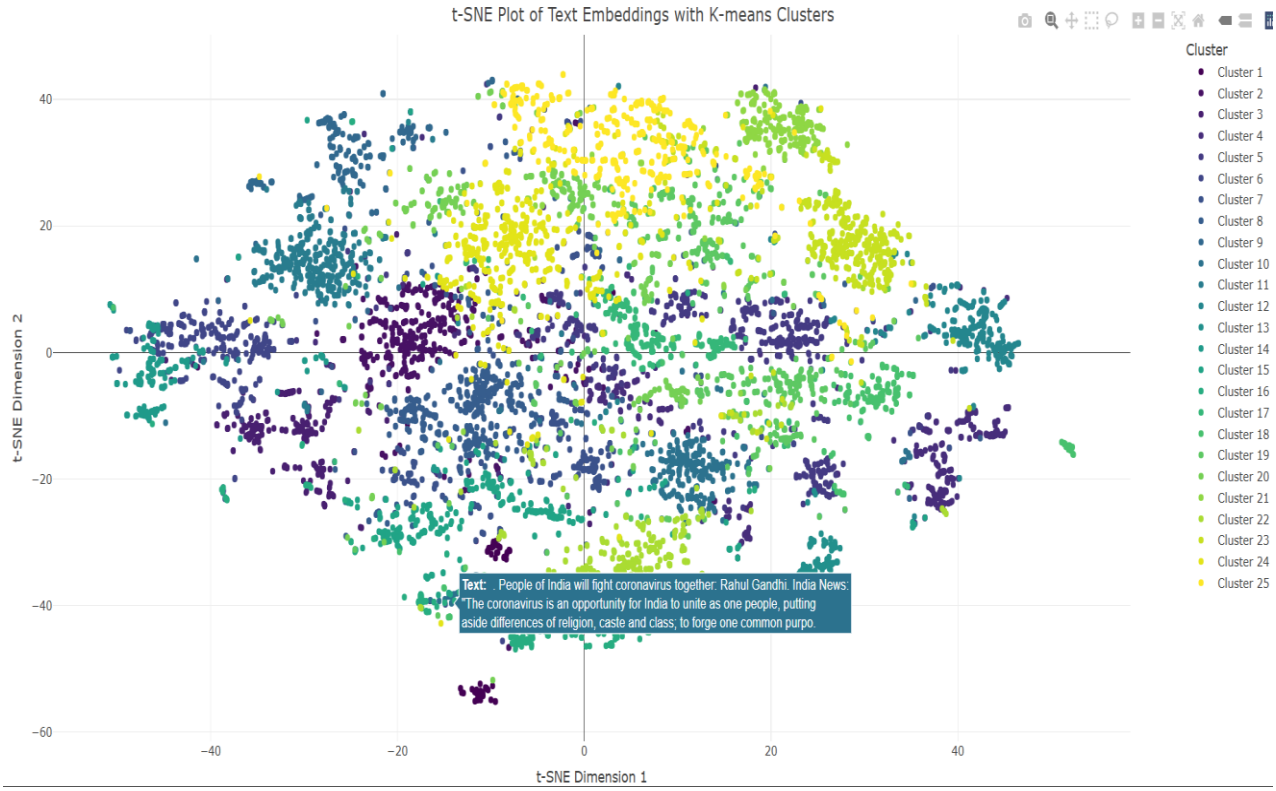


Figure 1 - *t-SNE plot of text embedding with K-means clusters*

cluster	numerosity	whiteness	centroid	label	label_cove
1	81	2993.992		Indian Railways' COVID-19 Response and Adaptations	1
2	430	129891.5		Adaptations and Innovations in Daily Life and Services During COVID-19 Lockdown	0.195349
3	247	36282.16		Philanthropic Responses to COVID-19 Pandemic	0.311741
4	359	87429.43		Global Political and Health Responses to COVID-19 Pandemic	0.239554
5	550	207987.3		COVID-19 Research and Technological Innovations	0.163636
6	282	50523.1		Sports Community Response to COVID-19 Pandemic	0.287234
7	341	82654.01		COVID-19 Impact and Response Measures Across Various Sectors and Countries	0.231672
8	464	134874.6		Impact of COVID-19 Lockdown on Agricultural and Migrant Communities	0.165948
9	277	52952.65		Recovery and Impact of COVID-19 on Public Figures and Global Communities	0.31769
10	301	53203.93		COVID-19 Response and Impact Analysis in India	0.305648
11	360	84271.57		Celebrity Responses and Public Engagement During the COVID-19 Pandemic	0.225
12	241	30498.29		Global Impact and Responses to COVID-19 Pandemic	0.327801
13	98	4558.512		Global Debate and Diplomacy Over Hydroxychloroquine Use and Export During COVID-19 Pandemic	0.77551
14	180	22561.64		Impact of COVID-19 on Global Sports Events and Athletes	0.45
15	333	71782.9		Global Economic Impact and Response Measures During the COVID-19 Pandemic	0.237237
16	346	63691.55		Indian Political Leadership's Response to COVID-19	0.234104
17	244	37358.58		Community and Government Initiatives for COVID-19 Prevention and Protection	0.340164
18	219	27279.46		Challenges and Strategies in COVID-19 Testing and Healthcare Response in India	0.365297
19	502	152205.8		COVID-19 Containment and Response Efforts in India	0.169323
20	336	72809.74		Community and Frontline Support During COVID-19 Crisis	0.208333
21	233	27178.19		COVID-19 Spread and Controversy Linked to Tablighi Jamaat Gatherings	0.309013
22	341	57160.43		Extended National Lockdown and Government Responses to COVID-19 in India	0.237537
23	435	81214.01		COVID-19 Crisis Management and Lockdown Measures in India	0.177011
24	458	137472.9		Enforcement and Impact of COVID-19 Lockdown Measures by Police and Authorities	0.168122
25	438	115152.8		COVID-19 Impact and Response in India	0.184932

Table 1 - *Labeled clusters*

Appendix D. Sentiment analysis for high engagement period

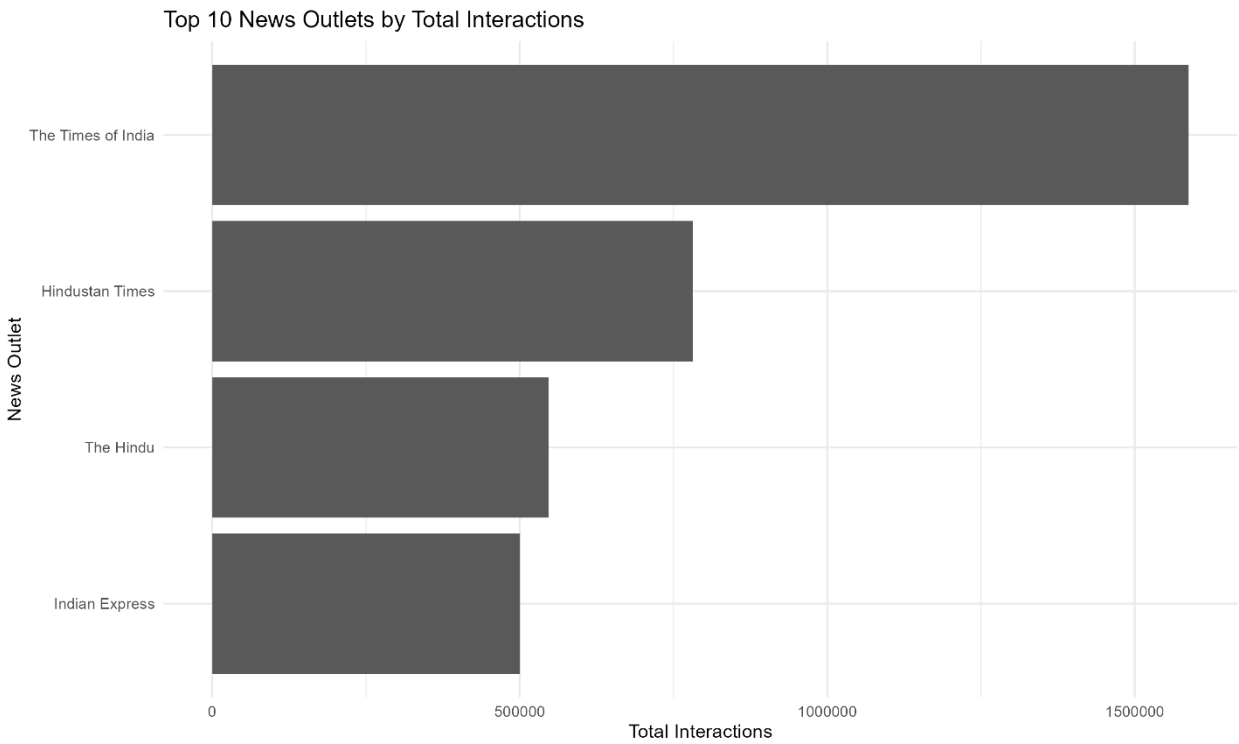


Figure 2 - *Top news outlets by total Interactions*

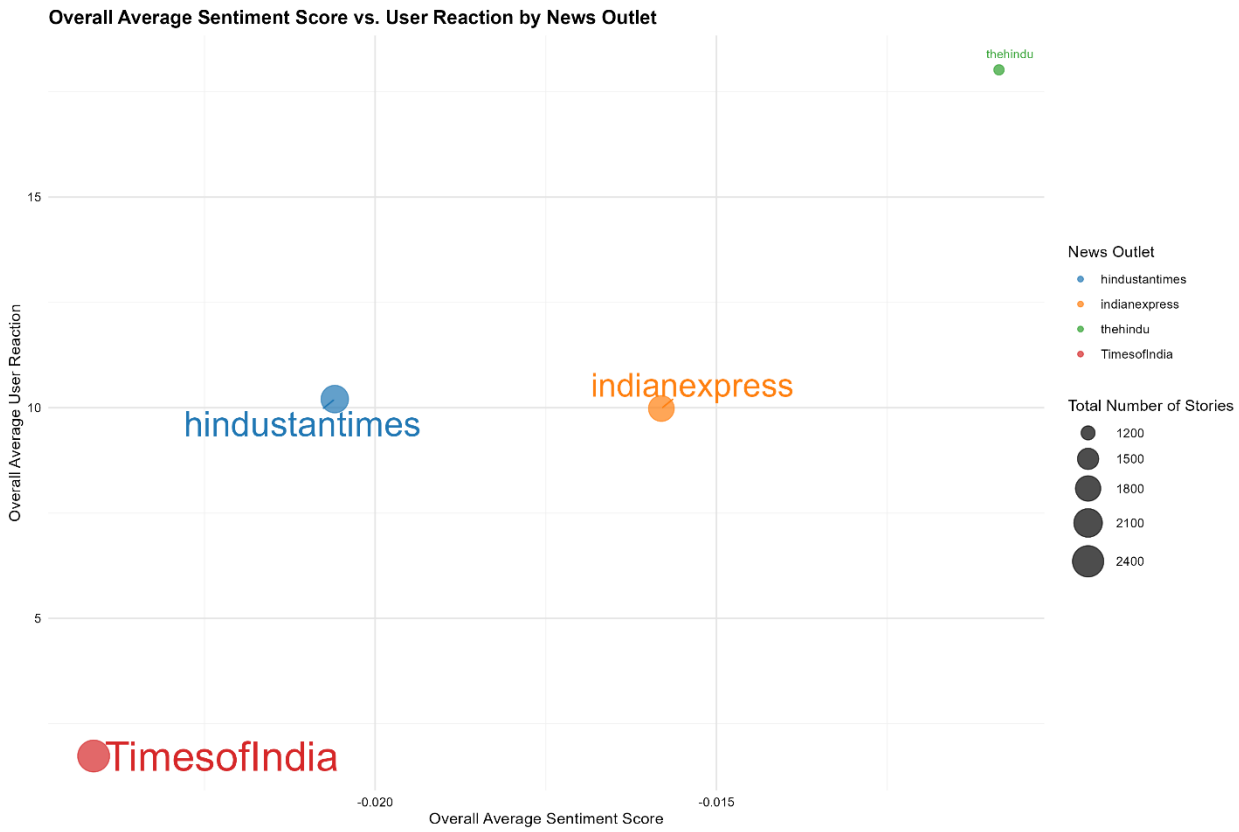


Figure 3 - *Overall Average Sentiment score vs. User reaction by News outlets*

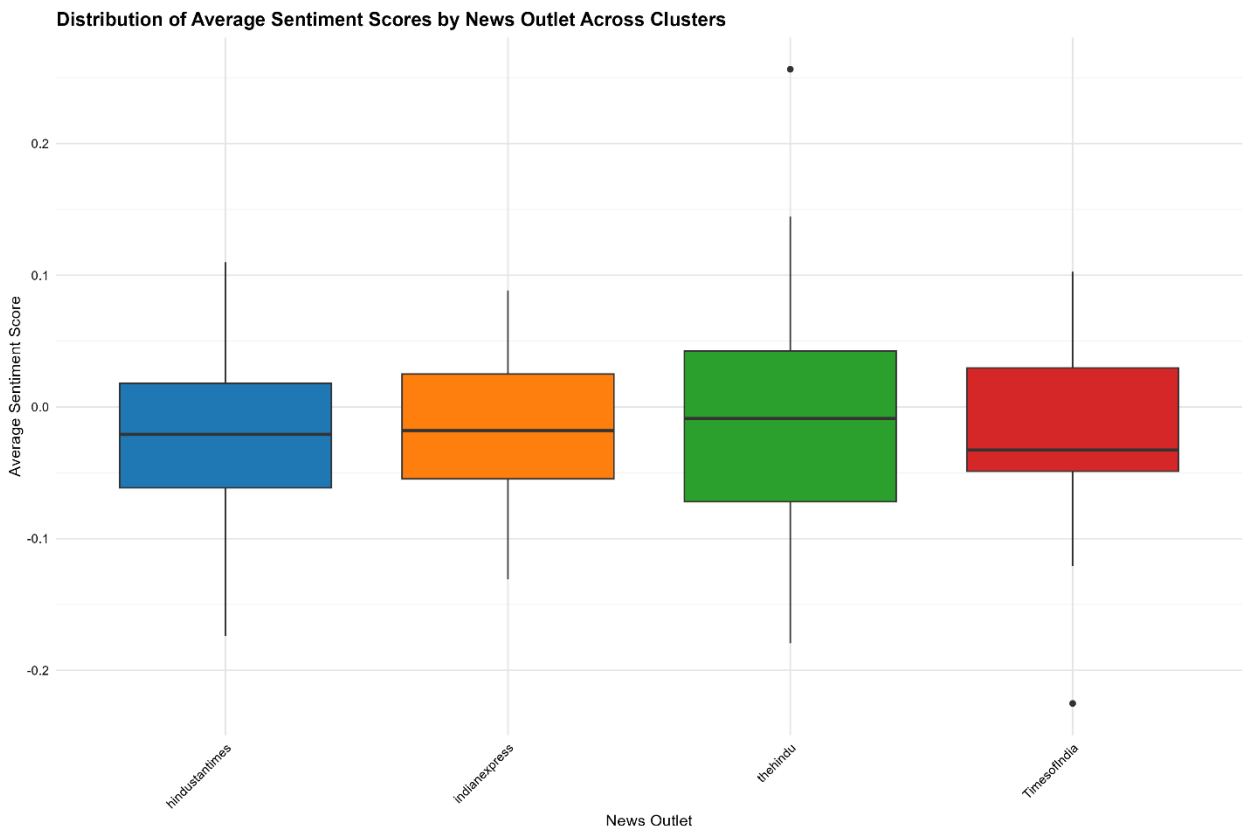


Figure 4 - *Distribution of Average Sentiment Score by News outlets across clusters*

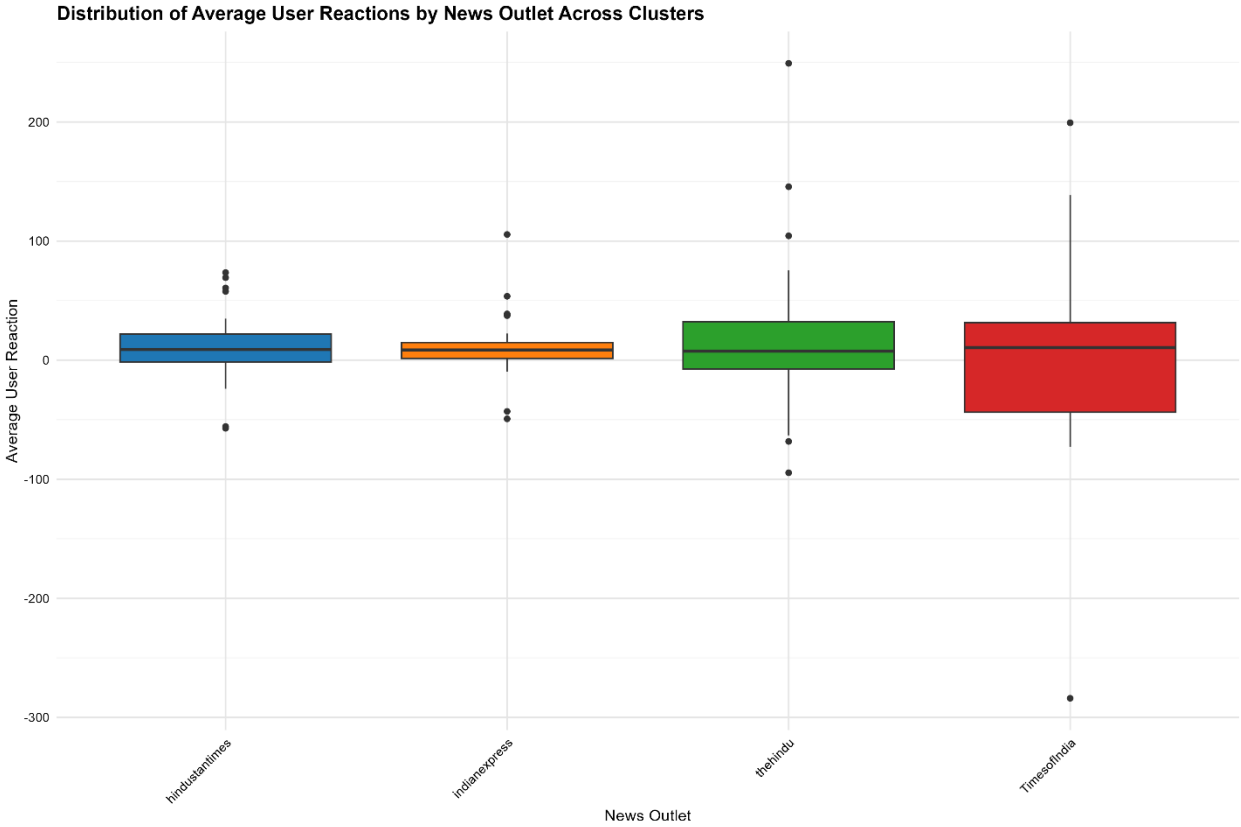


Figure 5 - *Distribution of Average User reactions by News outlets across clusters*

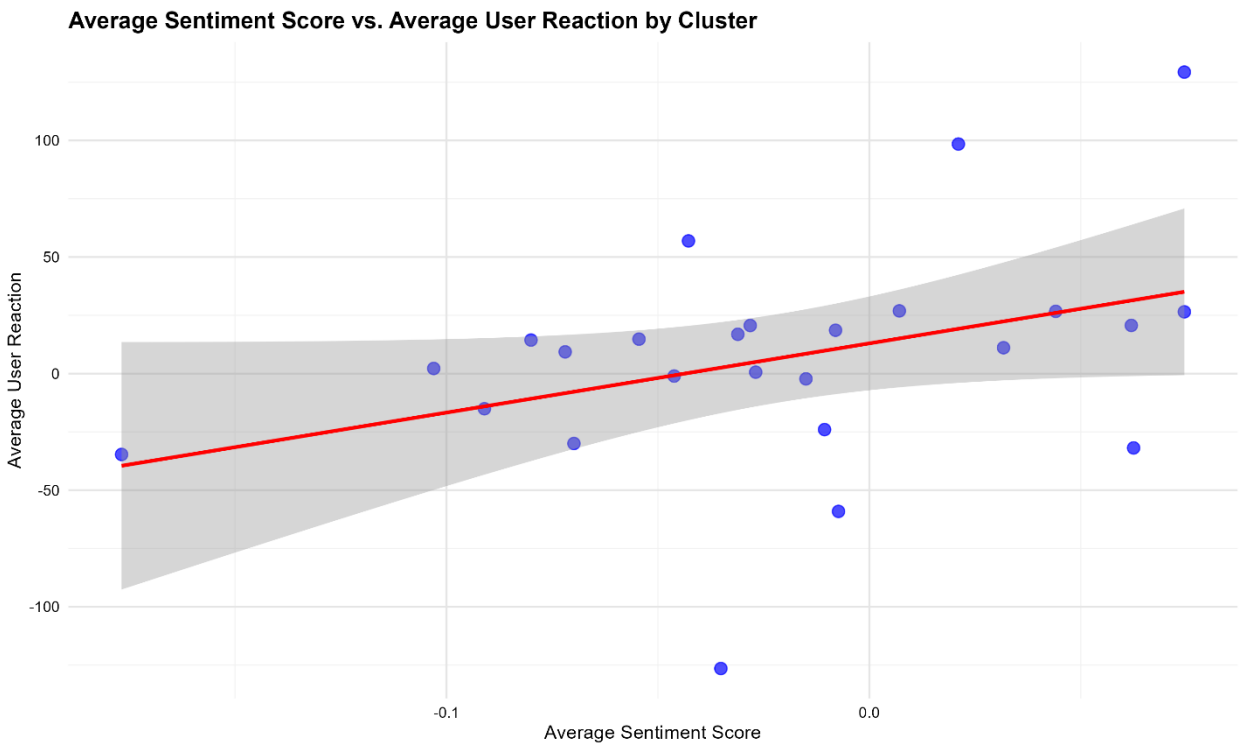


Figure 6 - *Average sentiment Score vs. Average user reaction by cluster*

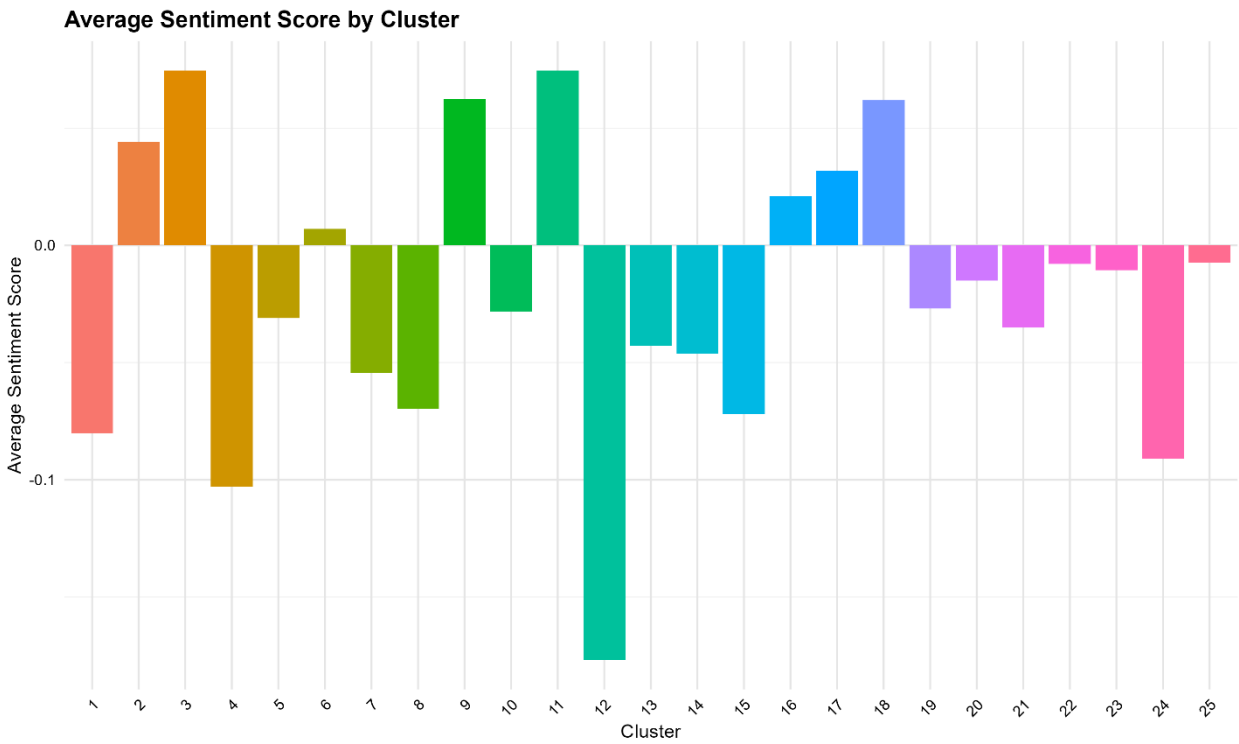


Figure 7 - *Average Sentiment Score by Clusters*

cluster	avg_sentiment	avg_user_reaction	total_stories
1	-0.080007987	14.3875	80
2	0.044070233	26.697733	397
3	0.074479675	129.3214286	224
4	-0.103014621	2.207317073	328
5	-0.031102376	16.86464646	495
6	0.007089784	26.90336134	238
7	-0.054477547	14.7827476	313
8	-0.069859102	-29.97986577	447
9	0.062484274	-31.87843137	255
10	-0.028170953	20.63448276	290
11	0.074483617	26.49859944	357
12	-0.176826237	-34.67873303	221
13	-0.042773971	56.91578947	95
14	-0.046161024	-1.060240964	166
15	-0.071925877	9.327922078	308
16	0.021051398	98.47484277	318
17	0.031725311	11.10434783	230
18	0.061939562	20.67156863	204
19	-0.02687967	0.614512472	441
20	-0.014991543	-2.251633987	306
21	-0.035114307	-126.490991	222
22	-0.007998208	18.59433962	318
23	-0.010598077	-24.01005025	398
24	-0.091022763	-15.07058824	425
25	-0.007299639	-59.10649351	385

Table 2 - *Cluster Sentiment score*

outlet	overall_avg_sentiment	overall_avg_user_rea	total_storie
TimesofIndia	-0.02412356	1.733023243	2473
hindustantimes	-0.020591758	10.20565979	1996
indianexpress	-0.015808138	9.982444005	1832
thehindu	-0.010862948	18.02211941	1160

Table 3 - *Overall Average Sentiment Score by News outlets*

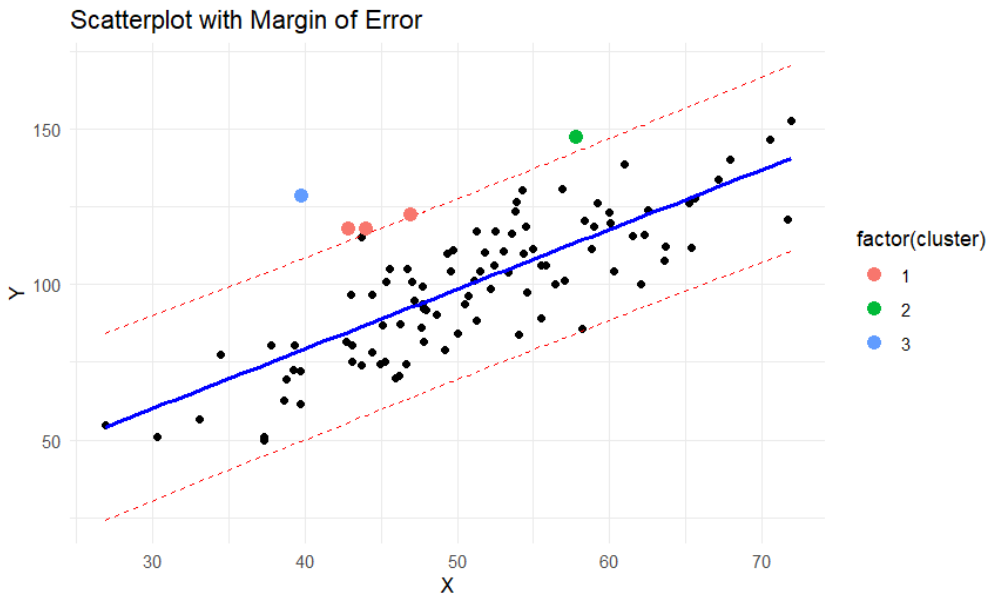


Figure 8 - *Scatterplot with Margin of Error*

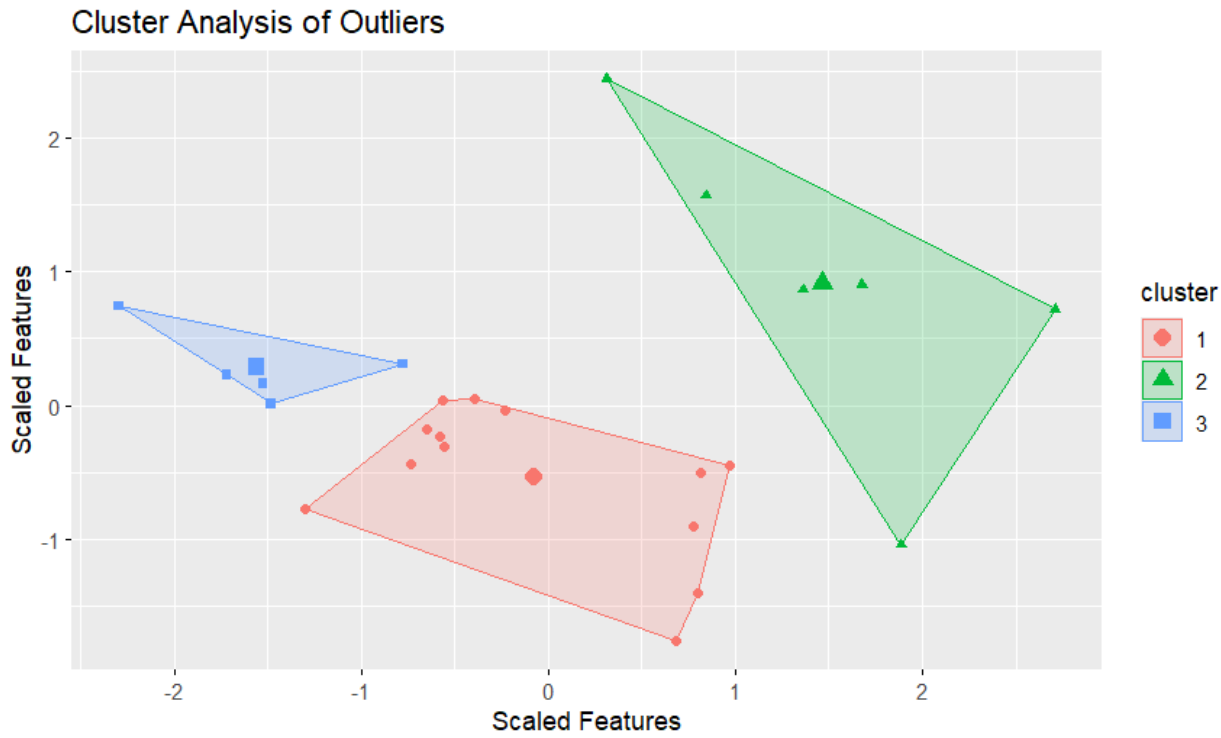


Figure 9 - *Cluster analysis outliers*

cluster	outlet	avg_sentiment	avg_user_reaction	story_count	ratio
3	TimesofIndia	-0.120926091	9.192307692	26	-0.01316
2	indianexpress	0.062591712	1.768518519	108	0.035392
1	TimesofIndia	-0.109793589	-2.152542373	118	0.051006
1	hindustantimes	-0.073326188	1.982142857	112	-0.03699
1	indianexpress	-0.130902269	3.85106383	47	-0.03399
3	thehindu	-0.126827693	11.2745098	51	-0.01125
3	hindustantimes	-0.06317076	7.025641026	156	-0.00899
2	thehindu	0.084719526	5.3	10	0.015985
1	thehindu	-0.071950222	3.890625	64	-0.01849
2	indianexpress	0.071178339	1.434782609	69	0.049609
1	thehindu	-0.060252918	4.682926829	82	-0.01287
2	TimesofIndia	0.10269955	10.53043478	115	0.009753
1	indianexpress	-0.106104378	-5.288888889	45	0.020062
1	TimesofIndia	-0.062620161	2.180555556	72	-0.02872
1	hindustantimes	-0.038744319	0.75862069	29	-0.05107
1	thehindu	-0.05795006	-2.444444444	9	0.023707
3	indianexpress	-0.117362975	10.04918033	61	-0.01168
2	thehindu	-0.087801965	-0.722222222	72	0.121572
2	hindustantimes	0.067947145	0.604166667	48	0.112464
1	TimesofIndia	-0.048818502	3.901315789	152	-0.01251
1	hindustantimes	-0.032570899	-0.937007874	127	0.034761
1	hindustantimes	-0.030456755	-1.578313253	83	0.019297
3	hindustantimes	-0.139540996	16.18867925	53	-0.00862
1	indianexpress	-0.039991237	2.571428571	112	-0.01555

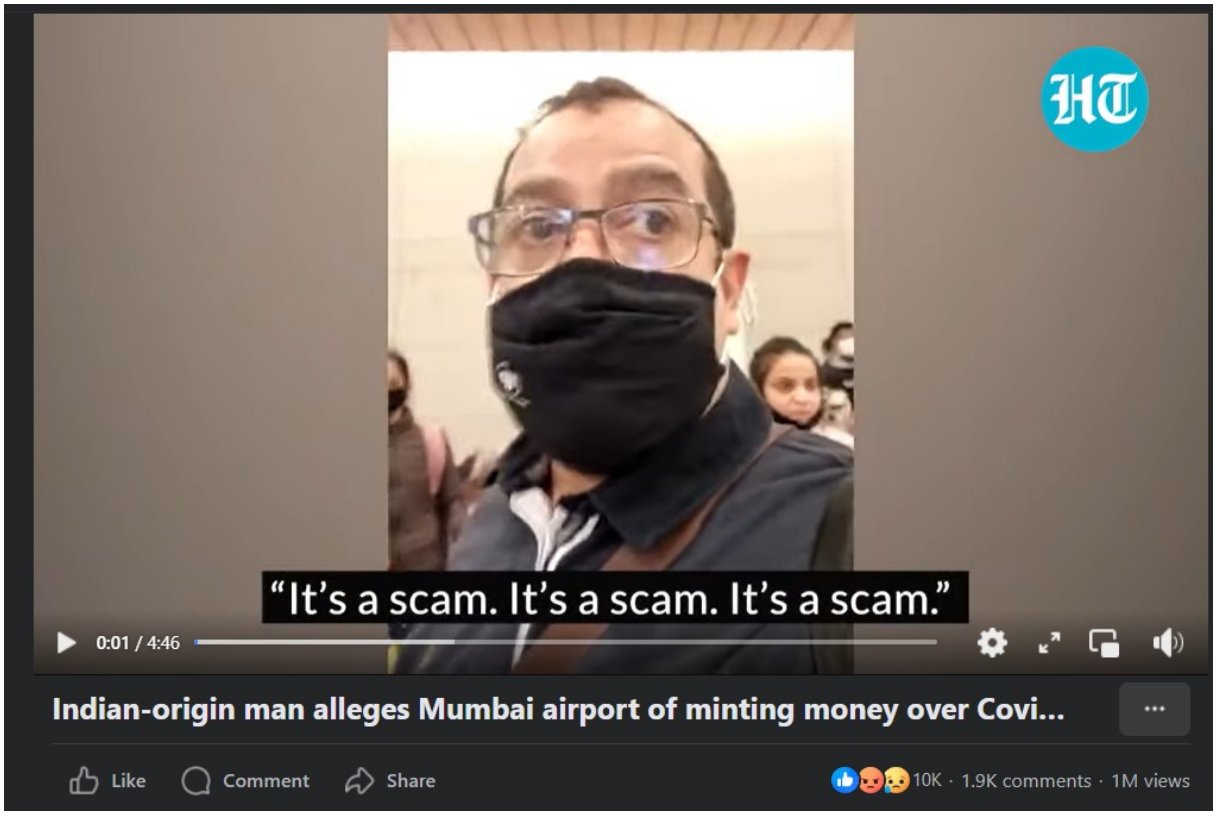
Figure 4 - *Outlier clusters with labels*

Appendix E: Documentation of Viral Facebook Posts During COVID-19 Coverage

This appendix provides comprehensive documentation of the viral Facebook posts referenced in Section 5.1.2, here are original URLs, screenshots, and reaction counts.

For Hindustan Times:

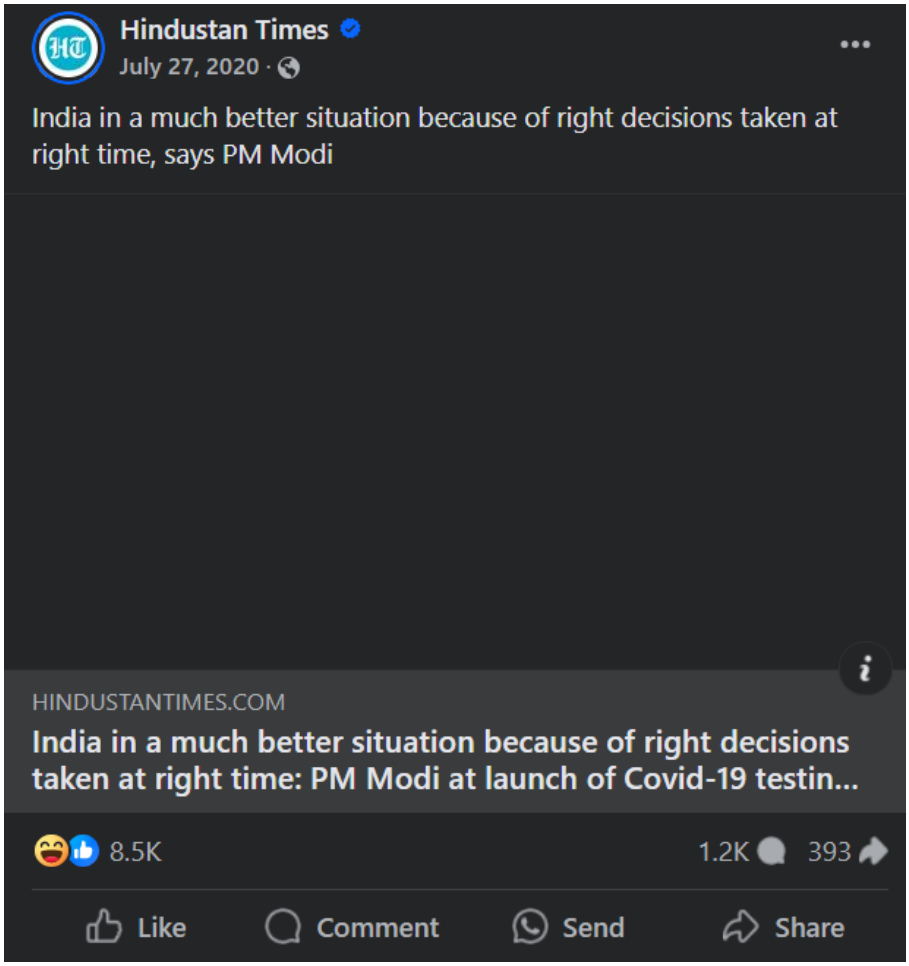
https://www.facebook.com/watch/?v=242770847992893



“An Indian-origin man alleged that Mumbai airport’s Covid test & quarantine protocol is a ‘scam’. Manoj Ladwa and his wife reached Mumbai on Dec 30 to attend his father-in-law’s funeral. The U.K. national narrated his version of events in a video on Facebook.”

Angry reaction- 1707, Date- January,04, 2022.

https://www.facebook.com/100064660902473/posts/10158210182833580/



Facebook Reaction “Haha”- 4311; Date- July 27, 2020

“Prime Minister Narendra Modi said Monday that India is in a much better situation in the fight against the Covid-19 pandemic because of the right decisions at the right time. Prime Minister Narendra Modi at the launch of the

ICMR's 'high throughput' coronavirus testing facilities in Mumbai, Kolkata and Nodia."

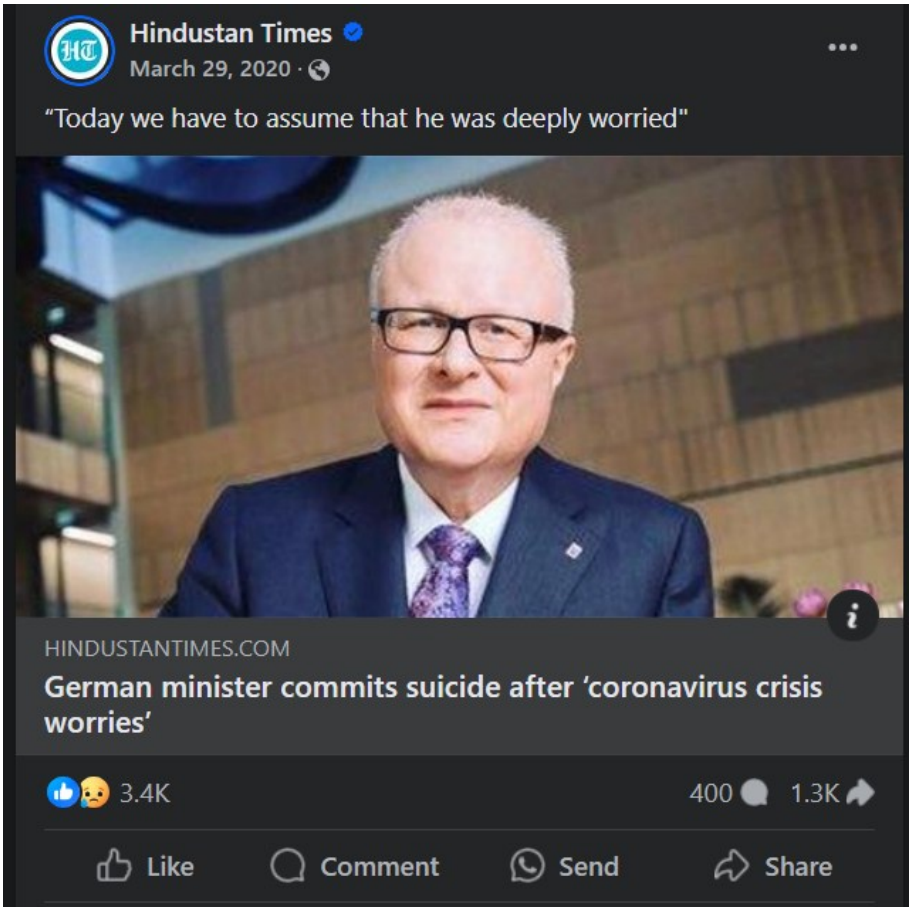
Notably, during the COVID-19 pandemic crisis, news related to public figures and their pandemic responses tended to generate particularly high engagement (Marino & Giglietto, 2023).

https://www.facebook.com/100064660902473/posts/10158294161623580/

Facebook reaction "Love"- 6244, Date- August,28,2020

"Actor Sonu Sood, who has been at the forefront of sending hundreds of migrant workers back to their homes, has now vowed to make travel arrangements for students appearing for JEE and NEET exams in September. Earlier, Sonu Sood had extended support to students' demand that NEET and JEE, scheduled to be held in September, should be postponed given the Covid-19 situation."

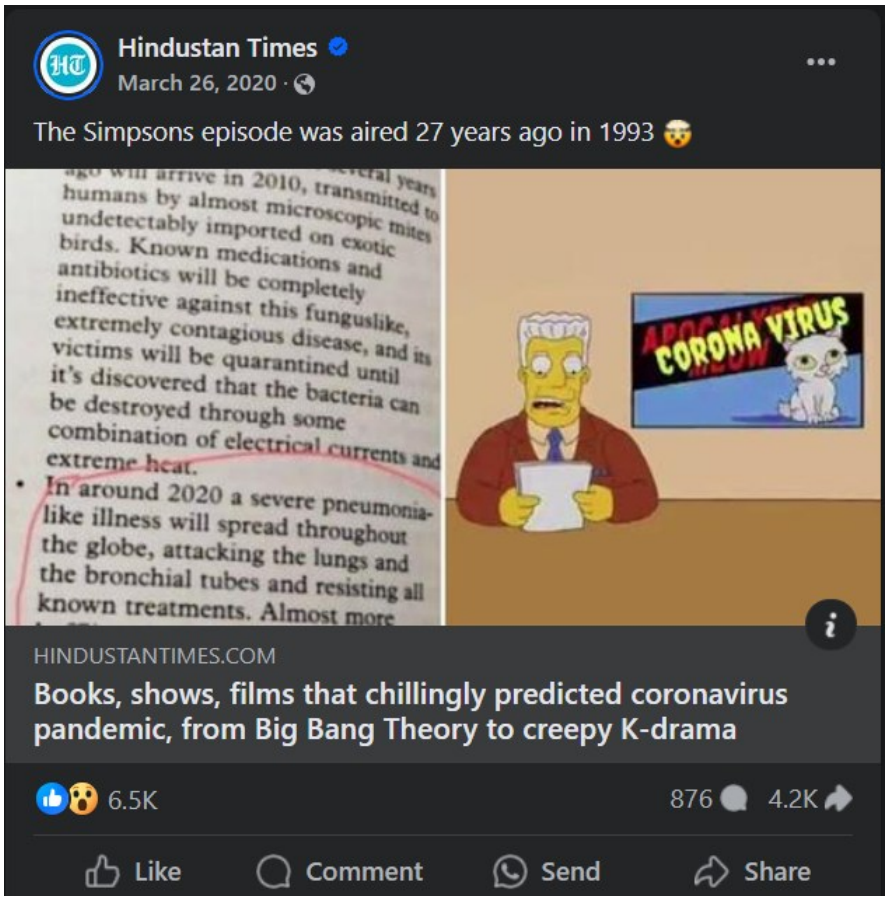
https://www.facebook.com/100064660902473/posts/10157810724998580/



Facebook reaction "Sad"- 1527, date- March,29,2020

"Schaefer, who was Hesse's finance chief for 10 years, had been working "day and night" to help companies and workers deal with the economic impact of the pandemic. Thomas Schaefer, the finance minister of Germany's Hesse state, has committed suicide apparently after becoming "deeply worried" over how to cope with the economic fallout from the coronavirus, state premier Volker Bouffier said Sunday."

https://www.facebook.com/100064660902473/posts/10157798233558580/



Facebook reaction "Wow"- 1045, Date- March,26,2020

"From a creepy K-drama and a chilling book about the end of the world to an Asterix comic and an episode of The Simpsons, here is all the pop-culture that 'predicted' the coronavirus pandemic. A thriller novel The Eyes of Darkness, written by Dean Koontz in 1981, mentioned a virus named Wuhan-400. The coronavirus originated in Wuhan and later spread across the world. In the novel, the virus was created in a lab. "The Wuhan-400 is the perfect weapon," a character says in the book. "It affects only human beings."

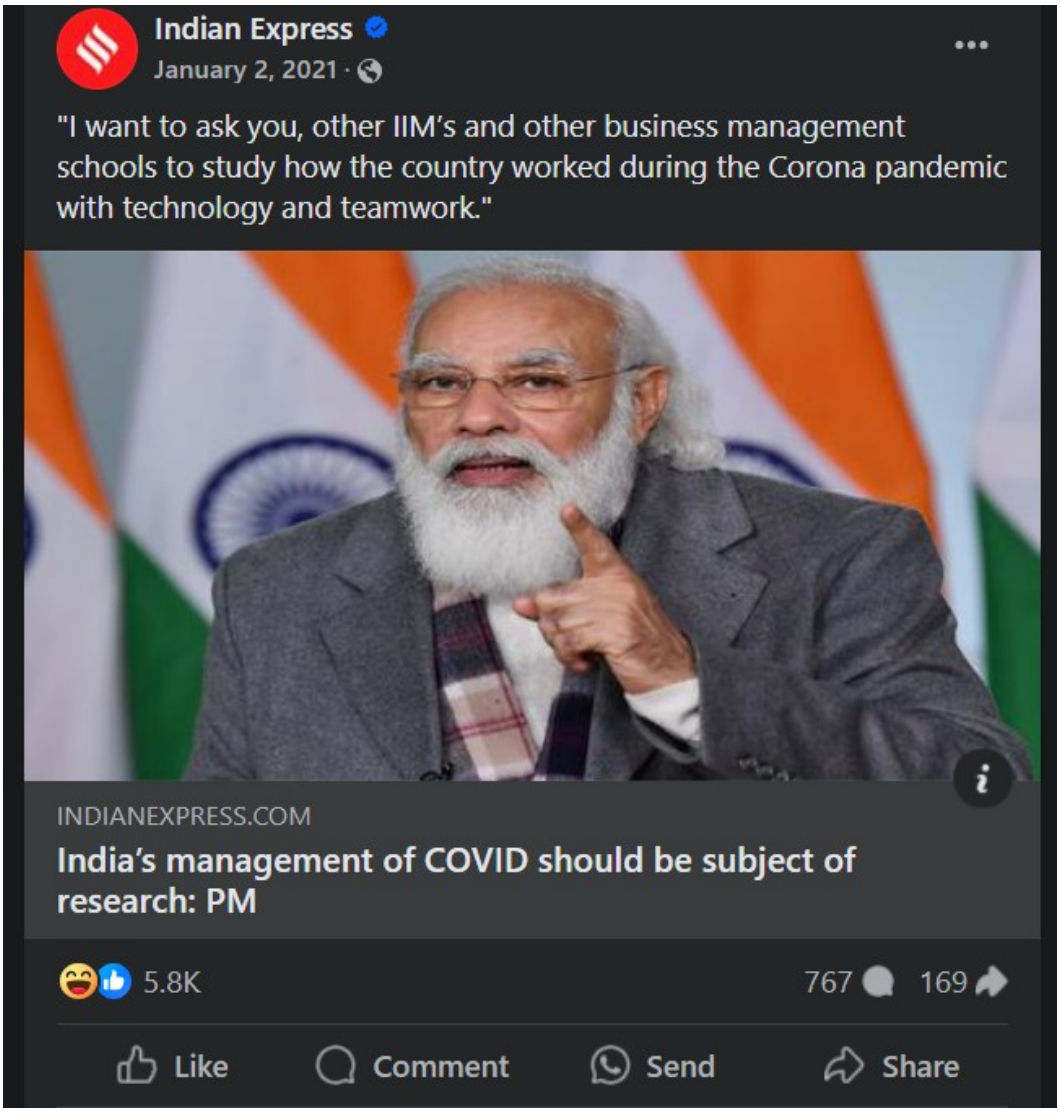
For Indian Express:

https://www.facebook.com/watch/?v=282284523036925

Facebook reaction "Angry"- 1465, Date- July,13,2020

"Prakash and his friends had violated curfew orders and were traveling in a car without masks."

https://www.facebook.com/100044214347061/posts/10159328727303826/



Facebook reaction "Haha"- 3410, Date- January,02,2021

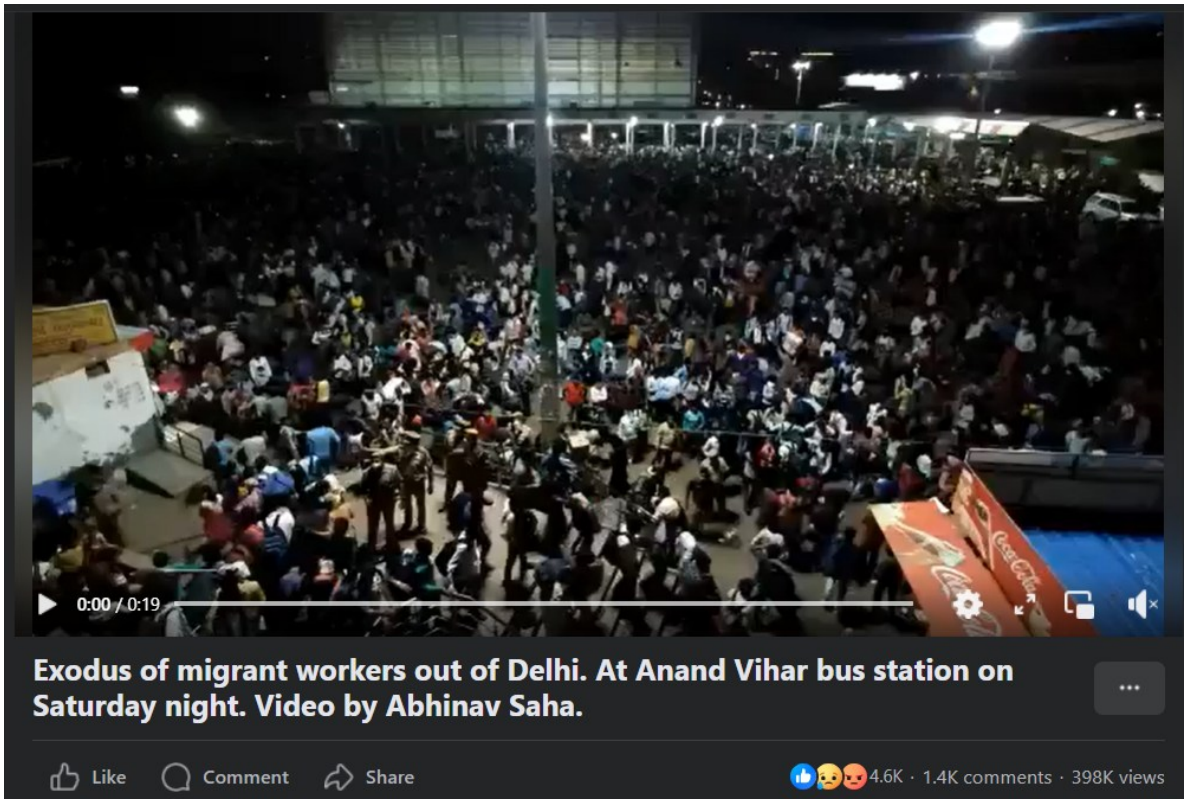
"Modi said, I want to ask you, other IIM, and other business management schools to study how the country worked during the Corona pandemic with technology and teamwork. How steps were taken for the protection of 130 crore people." He urged IIMs and other B-schools in India to research the efforts that were taken during the COVID period and document the transformation and innovations adopted for capacity building during the time."

https://www.facebook.com/100044214347061/posts/10159124917783826/

Facebook reaction "love"- 2227, Date- October,16,2020

"Migrant mother with a child- A clay idol of a migrant mother with a child in her arms and her three other children trailing her will be worshipped as goddess Durga at a community puja in Kolkata. The subject narrates the plight of millions of lockdowns that hit migrant workers."

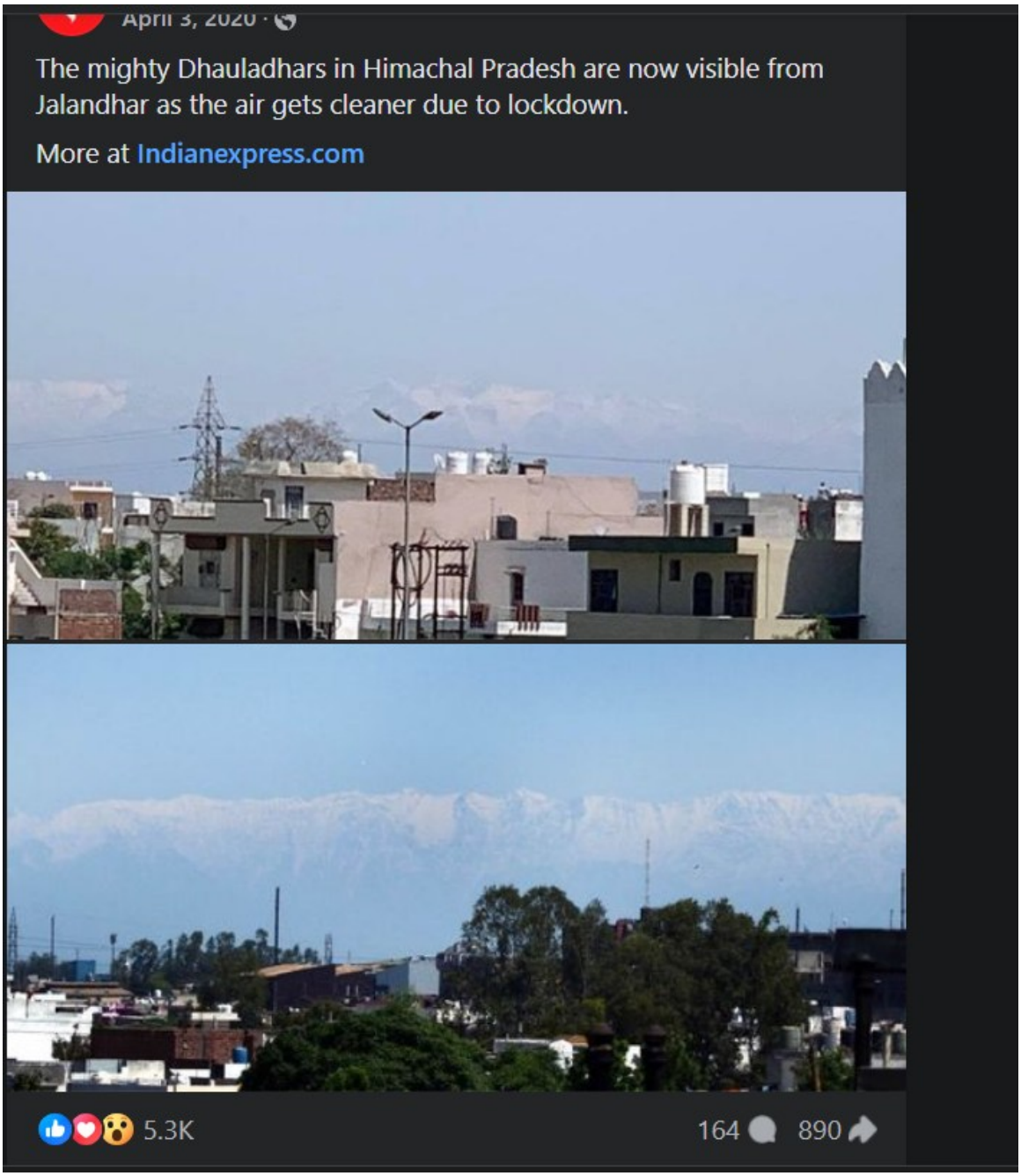
https://www.facebook.com/watch/?v=205622760764205



Facebook reaction "Sad", Date-March,28,2020

"Exodus of migrant workers out of Delhi. At Anand Vihar bus station on Saturday night. Video by Abhinav Saha."

https://www.facebook.com/163648403825/posts/10158488101648826

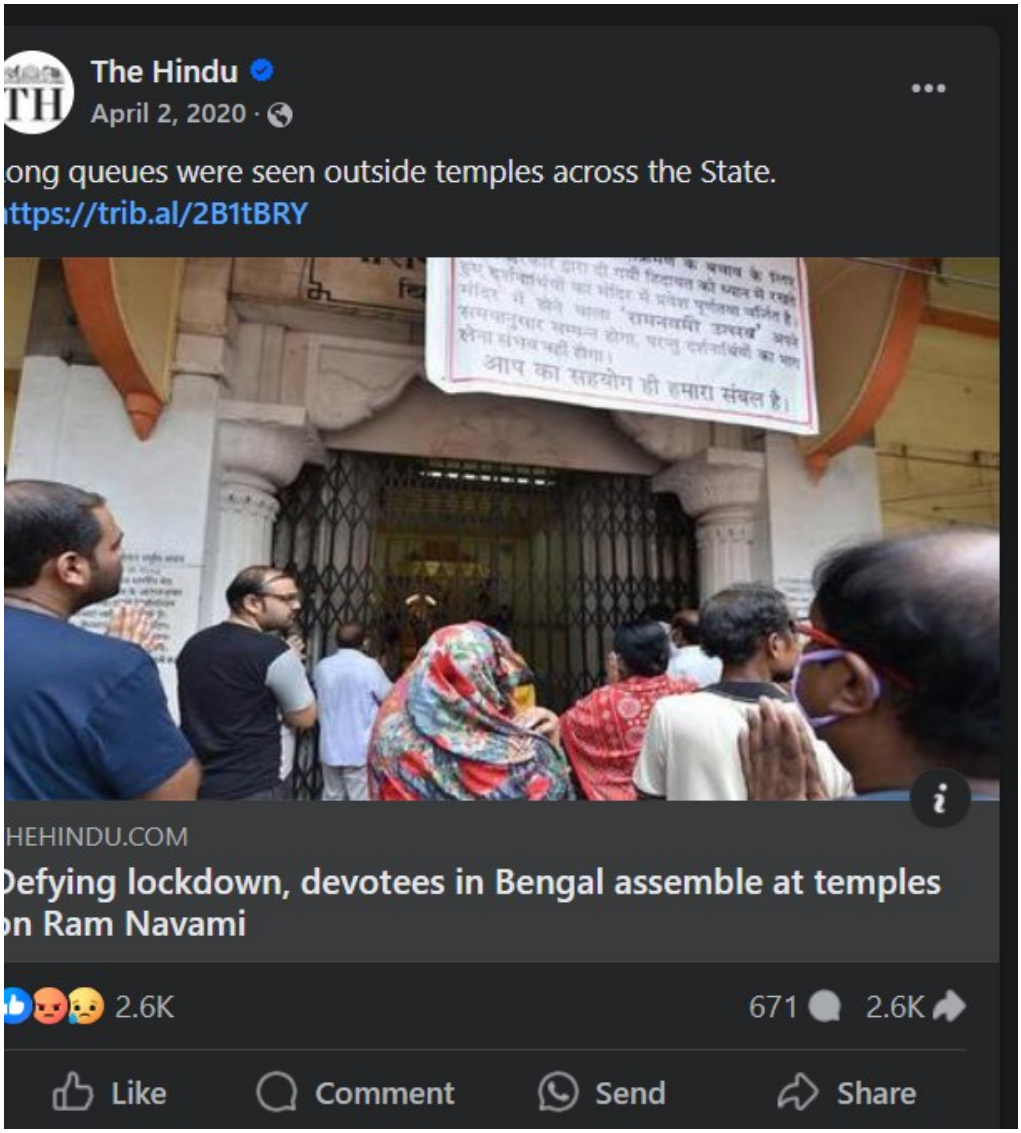


Facebook reaction “Wow”- 519, Date- April,03,2020

“The mighty Dhauladhars in Himachal Pradesh are now visible from Jalandhar as the air gets cleaner due to lockdown.”

For The Hindu:

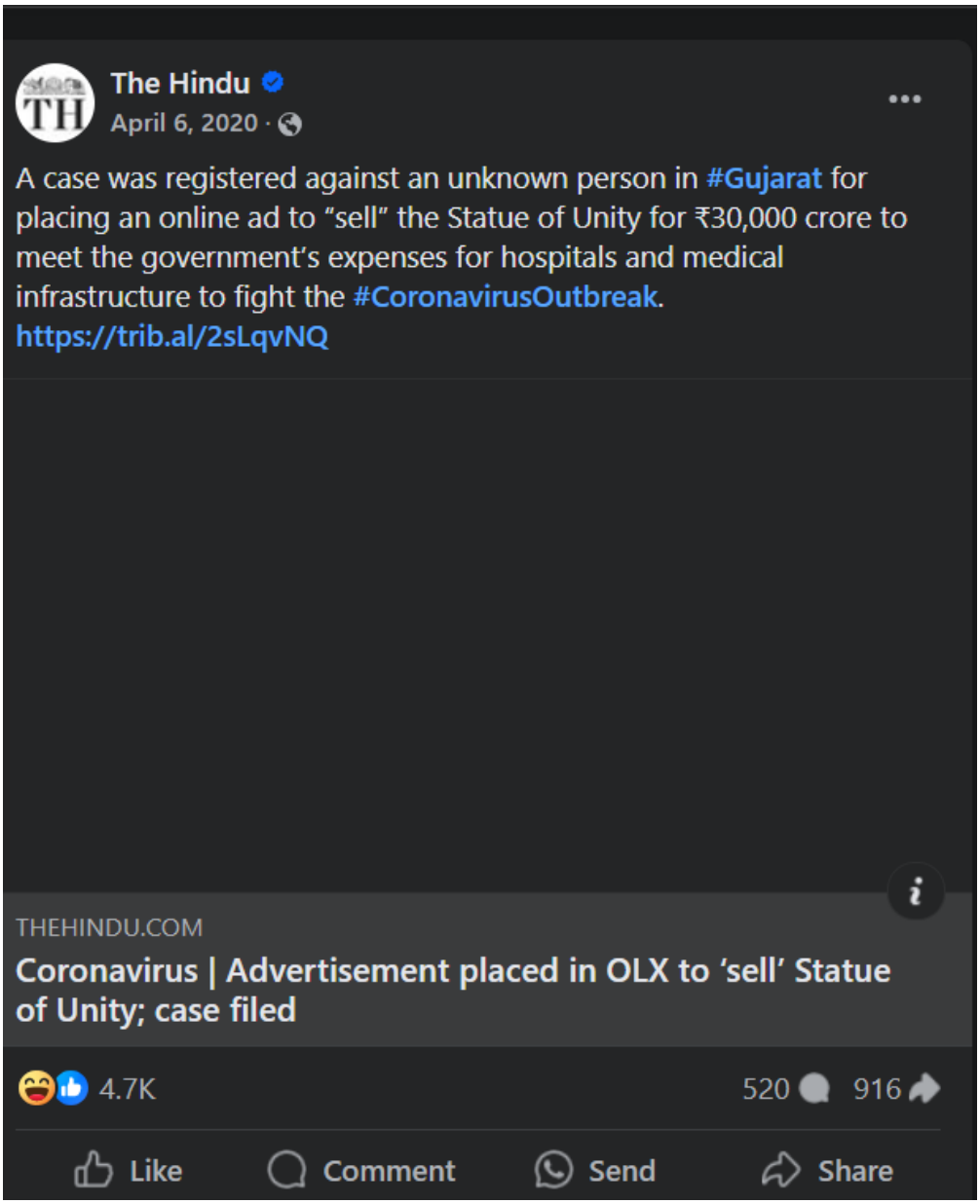
https://www.facebook.com/163974433696568/posts/3051180221642627



Facebook reaction "Angry"- 1077, Date-April, 02,2020

"Amid chants of 'Jai Sri Ram', hundreds of devotees assembled in temples in various parts of West Bengal on the occasion of Ram Navami on Thursday, giving a thumbs down to social distancing norms prescribed by the government during the ongoing nationwide lockdown period"

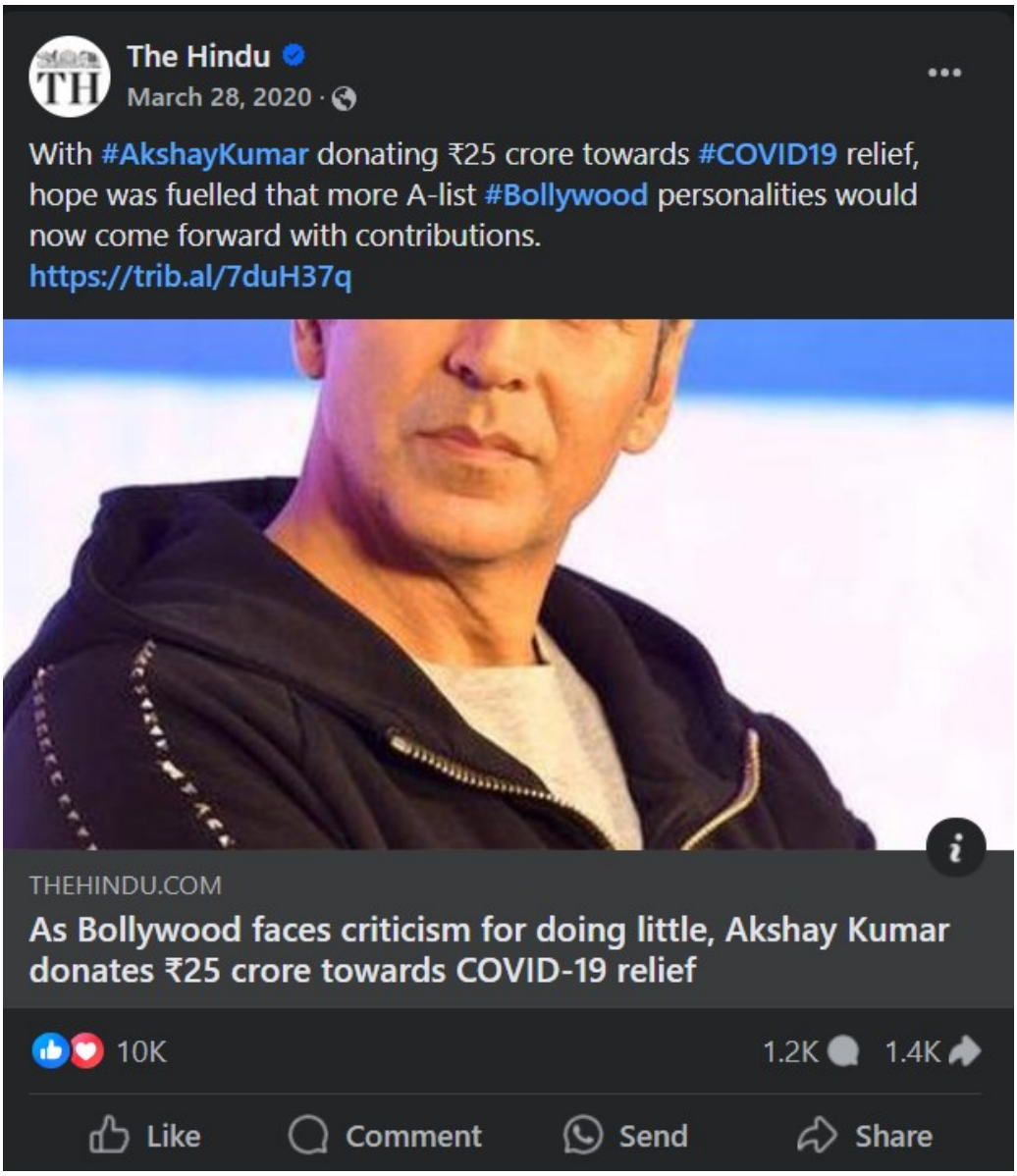
https://www.facebook.com/163974433696568/posts/3059422770818372



Facebook reaction "Haha"- 2913, Date- April 06, 2020

"A case was registered against an unknown person in Gujarat for placing an online advertisement to "sell" the Statue of Unity in Kevadiya in Narmada district for ₹30,000 crore to meet the government's expenses for hospitals and medical infrastructure to fight the coronavirus outbreak ."

https://www.facebook.com/163974433696568/posts/3039958509431465



Facebook reaction "Love"- 2216, Date- March 28, 2020

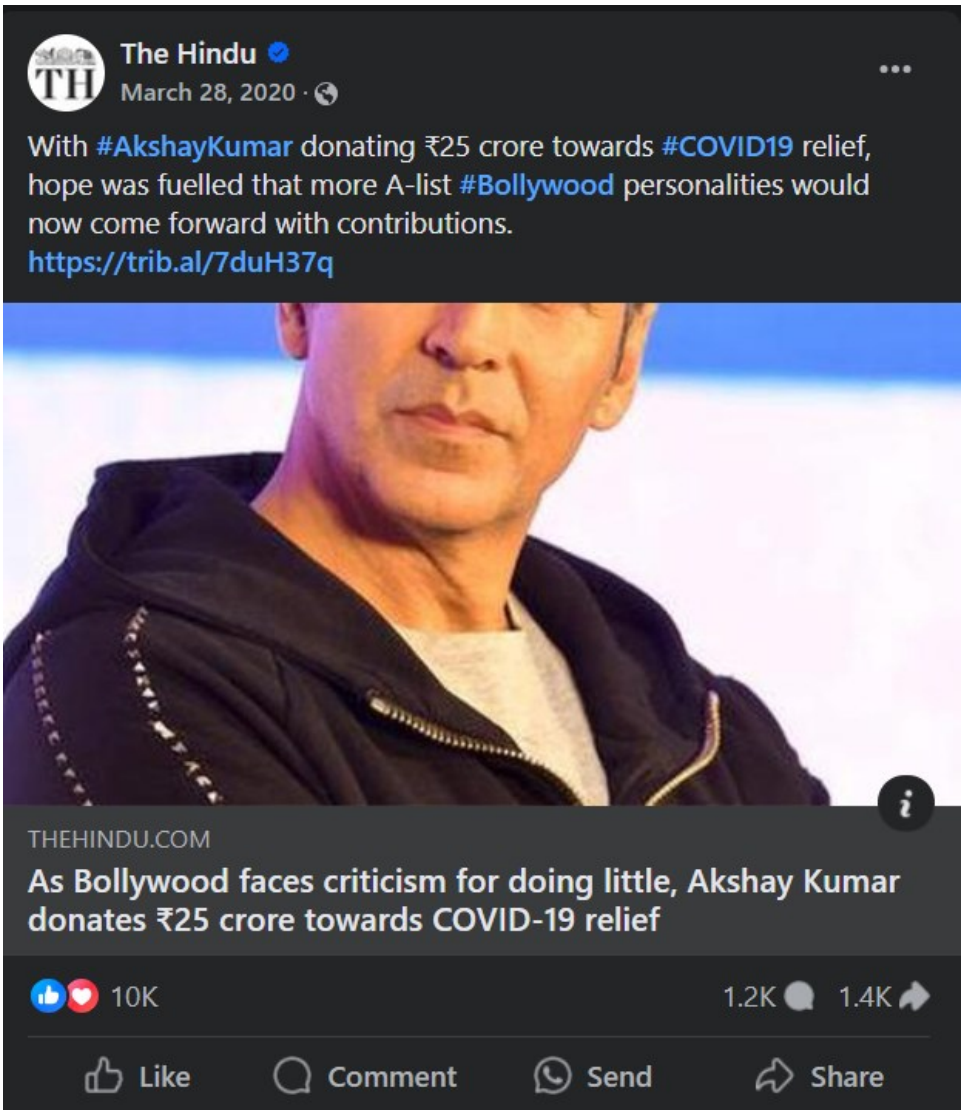
"Akshay Kumar has pledged the amount to the newly formed Prime Minister's Citizen Assistance and Relief in Emergency Situations Fund. With Akshay Kumar donating ₹25 crore towards COVID-19 relief, hope was fuelled that more A list Bollywood personalities would now come forward with contributions."

https://www.facebook.com/163974433696568/posts/3160406917386623

Facebook reaction "Sad"- 3021, Date- May 17, 2020

The face of a tragedy: The photo of Rampukar Pandit weeping by a road in Delhi was widely shared across all media. Rampukar Pandit, who became a snapshot of India's migrant tragedy with his photograph sobbing by a road in Delhi, is back in Bihar, broken at not being able to see his son before he died."

https://www.facebook.com/163974433696568/posts/3039958509431465



Facebook reaction “Wow”- 190, Date- March 28, 2020

The Times of India:

https://www.facebook.com/26781952138/posts/10158510444057139

Facebook reactions "Angry"- 4833, Date- March 25, 2020

"In what is turning out to be a recurring situation all over the country, Ernakulam in Kerala also saw youth thrashing cops because they were stopped from stepping outside during the 21-day lockdown. The cops had tried to stop 2 youths from stepping out but instead, the two grabbed the collar of the policeman and started a fight."

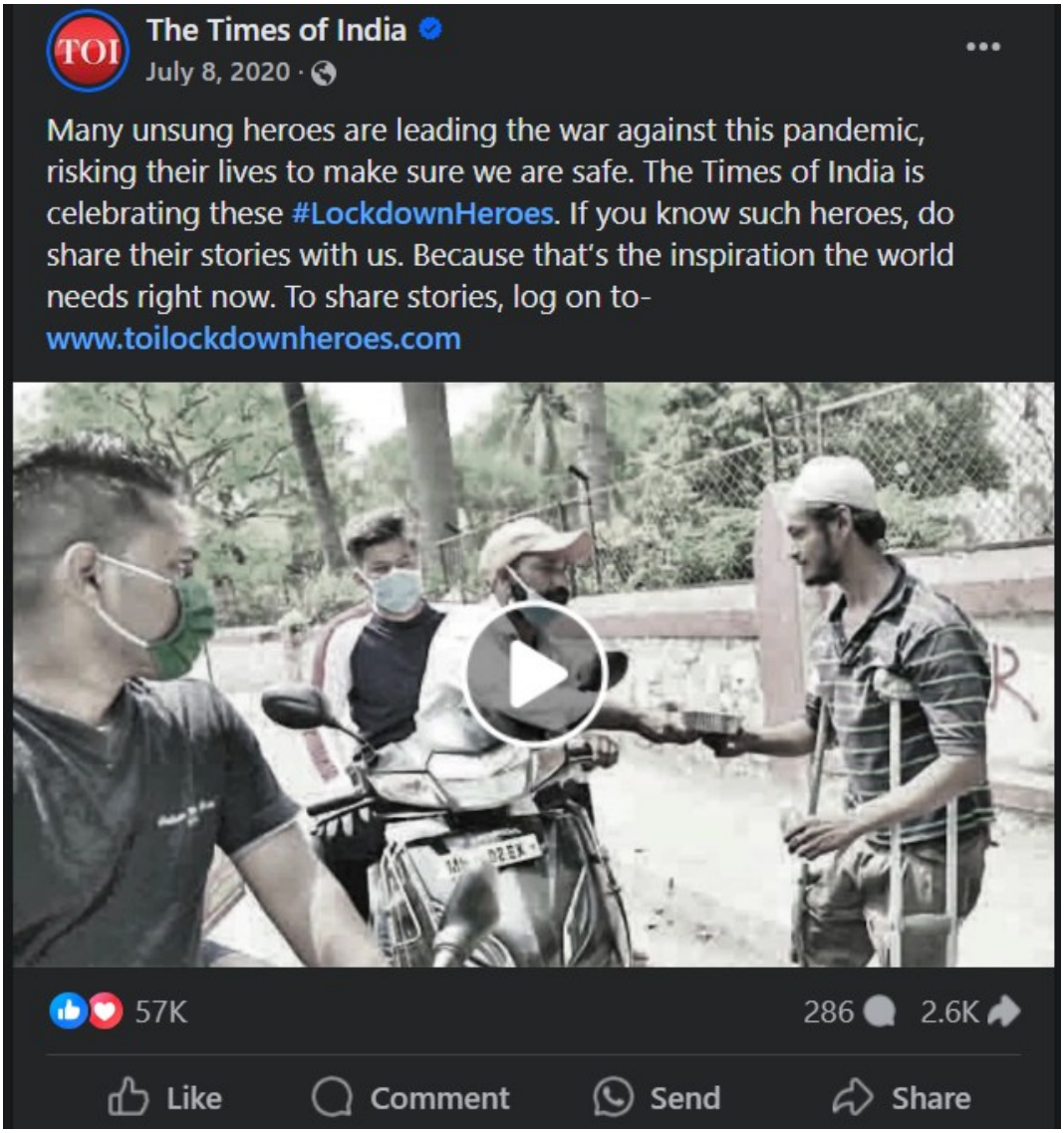
https://www.facebook.com/26781952138/posts/10159210205777139

Facebook reactions "Haha"- 5624, Date- October 22, 2020

BJP promises free Covid vaccine to people of Bihar in election manifesto

"After releasing the election song, the Bharatiya Janata Party on Thursday released its sankalp patra for Bihar elections. Union finance minister Nirmala Sitharaman released the party's manifesto saying the BJP will provide citizens of the state free coronavirus vaccine approved by ICMR and around 19 lakh jobs for youths of the state."

https://www.facebook.com/26781952138/posts/10158920319282139



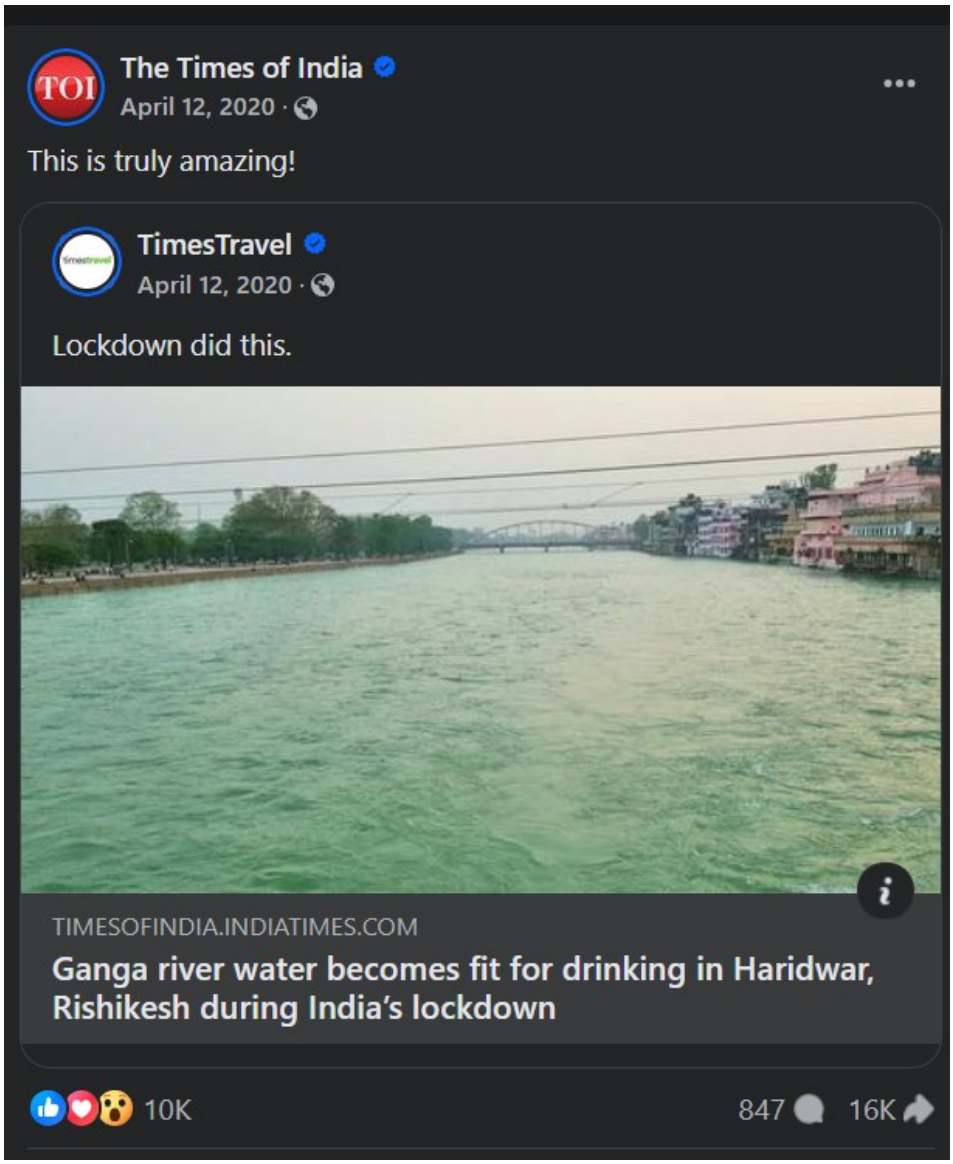
Facebook reaction "Love"- 4259, Date-July 08, 2020

https://www.facebook.com/26781952138/posts/10158513833572139

Facebook reactions "Sad"- 4583, Date-March 26, 2020

"Labourers and migrant workers, who move from one place to another for work, are facing the brunt of lockdown amid coronavirus."

https://www.facebook.com/26781952138/posts/10158584310062139



Facebook reaction "Wow"- 682, Date- April 12, 2020

"News has it that Ganga waters at Rishikesh and Haridwar have become very clean according to the observation made by BD Joshi, Environmental Scientist and Ex-professor at the Gurukul Kangri University. According to Joshi, it is after a long time that Ganga water has become good for *achaman* (ritual sipping) in Haridwar. Joshi also added that the cause behind cleaner Ganga water is a 500 percent decrease in total dissolved solid (TDS), industrial effluent, *dharmashalas*, and sewage from hotels and lodges."