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Social Media Narratives : Addressing Extremism in Middle Age

D4.3 – Sentiment Analysis Report

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Abstract	This study examines the emotional and moral dynamics that drive engagement with disinformation, conspiracy theories, and polarizing content in online discussions. Through a sentiment analysis of user comments on Daily Mail articles, we explore how different emotions and moral framings shape public discourse. A key objective is to demonstrate the correlation between the attractiveness of polarizing content, its moral framing, and the emotional responses it elicits. Findings indicate that negative emotions dominate user comments, especially in reaction to perceived violations of moral values such as fairness, authority, and purity. Specific topics generate the most intense emotional and moralized responses, reinforcing ideological divisions and strengthening group identities. A crucial contribution of this study is its innovative approach, which systematically investigates the interplay between moral values and emotions in online discourse. To our knowledge, this relationship has not yet been extensively examined, particularly not with the application of Large Language Models (LLM) to analyze large-scale user-generated data. Our results highlight the limitations of traditional countermeasures such as fact-checking and content correction, which often fail to address the deeper emotional and moral concerns that make disinformation and polarizing narratives so compelling. Instead, we propose a multi-dimensional strategy that combines content regulation, digital literacy, and psychological inoculation to mitigate the impact of polarizing content effectively. By providing new insights into the mechanisms that sustain online polarization and misinformation, this study contributes to a deeper understanding of how digital discourse is shaped by moral and emotional dynamics.

Key Words	Social media, harmful content, disinformation, conspiracy theories, online radicalisation, social networks, semantic networks, natural language processing, sentiment analysis, moral foundations theory

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1.0	2025/02/24	Christian Gulas, Paul Poledna, Harald Katzmair		Submitted version

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1. Objective

In the first part of this research report, documented in Deliverable D4.2, we examined the network structures and textual patterns of conspiracy theories, polarizing content, and disinformation as it shows up in Telegram messages, YouTube videos, and Daily Mail user comments. A central finding of this analysis was that such content is frequently morally framed—it engages with moral values, highlights their perceived violation, and evokes strong emotional reactions in its audiences. While the success and attractiveness of conspiracy theories and disinformation have multiple causes, one key aspect we investigate in this study is their emotional and moral appeal. Our premise is that moral values, as conceptualized by Jonathan Haidt's Moral Foundations Theory (Haidt, 2013), are closely intertwined with emotions and sentiments (Haidt, 2003). Specifically, we argue that the violation of moral values generates strong moral emotions and that analyzing these emotions provides deeper insights into the appeal and dissemination of disinformation and conspiracy narratives.

In this context, we conduct a sentiment analysis of Daily Mail user comments in response to news articles. We consider user comments an especially valuable dataset for this study because a key motivation for users to engage in online discussions is the expression of emotions (Bagić Babac, 2023). Unlike journalistic reporting or political statements, user comments can be immediate emotional reactions to events. In many cases they offer a rich resource for examining which emotions are triggered by specific news topics and how moral values and their perceived violations shape emotional discourse.

Building on the psychoanalytic perspective outlined in Deliverable D4.2, we conceptualize conspiracy theories and polarizing content as "substitute containers" for unprocessed emotions, following the framework of Wilfred R. Bion (Mertens, 2018). Conspiracy narratives, disinformation, and polarizing content provide coherence to scattered, emotionally charged but unconnected information, transforming them into structured narratives. In Bion's terminology, these narratives facilitate the conversion of raw, chaotic "beta elements" into processable "alpha elements", allowing individuals to psychologically manage their distress. By acting as a projection surface, conspiracy theories provide individuals with an explanatory model that externalizes fears, anxieties, and moral grievances onto identifiable culprits. Their virulence increases in times of crisis and uncertainty, when emotions run high and when people struggle to process the complexity of unfolding events.

A central reason for the power of these emotions is that they are often responses to real or perceived violations of moral values. While news events may trigger a variety of emotions, we argue that emotional reactions are particularly intense when events appear to transgress deeply held moral principles. This is because moral values constitute the foundation of human social life. According to Haidt, they serve three key functions: they enable cooperation and group cohesion, they guide human behavior and social interactions, and they shape individual and collective identities (Haidt, 2013, pp. 219ff.). Moral values determine who we trust, what we consider fair or just, and how we define belonging to a community. Because they are so fundamental, their violation provokes strong emotional responses, ranging from anger and moral outrage to fear and disgust (Hutcherson et al., 2011). Crisis events frequently involve moral conflict, and conspiracy theories provide narratives that structure and channel these emotional reactions.

To make sense of these moral transgressions, conspiracy theories follow a distinct moral framing strategy. They focus on negative events – those that cause harm, instill fear, or pose a threat – and frame them as deliberate acts of moral violation by malevolent actors. This structure simplifies complexity by assigning clear cause-and-effect relationships, identifying culprits, and attributing intent. These moralized explanations help individuals process distressing events by reinforcing black-and-white distinctions between good and evil. By constructing coherent explanations for chaotic emotions, conspiracy theories provide psychological relief, making overwhelming social and political transformations more comprehensible and emotionally manageable (Douglas et al., 2017).

This study aims to deepen our understanding of how moral emotions shape engagement with online disinformation. **We hypothesize that different moral values correlate with distinct emotional responses.** Violations of Care and Harm, such as instances where peer group is subjected to suffering, are likely to trigger feelings of fear and sadness. When individuals perceive breaches of Fairness and Cheating, such as cases of political corruption or election fraud, they are more inclined to experience anger and resentment. Similarly, transgressions related to Sanctity and Purity, including concerns about contamination or moral decay, tend to elicit emotions of disgust and repulsion (Landmann et al., 2018).

Since user comments are key expressions of emotional responses, we analyze them as indicators of how moral violations are emotionally framed in online discourse.

Against this background, we address the following three core research questions:

1. **Prevalence of Emotional Expressions in User Comments**: Which emotions are most frequently expressed in user comments responding to news content? What types of emotional responses (e.g., anger, fear, disgust) dominate discussions?
2. **Association Between Topics and Emotional Responses**: Which topics are most strongly associated with specific emotions? Do particular themes (e.g., immigration, vaccines, political elites) correlate with specific emotional reactions?
3. **Connection Between Moral Values and Emotional Expressions:** How do moral values and perceived moral violations relate to these emotional expressions? Are certain moral foundations (e.g., Care, Fairness, Authority) more strongly linked to specific emotions? How do users frame political and societal issues in terms of moral transgressions?

By addressing these questions, the following analysis seeks to advance our understanding of the moral and emotional dynamics that drive engagement with disinformation and conspiracy theories. **Rather than focusing solely on the factual accuracy of online content, we emphasize its emotional and moral appeal.** Understanding the interplay between moral values, emotions, and digital content is crucial for developing more effective strategies to “counter” harmful content—not only by providing factual corrections but by addressing the underlying emotional and moral concerns that make these narratives so compelling.

2. Methodology

To analyze the emotional dynamics, present in user comments, we employed a sentiment analysis, a computational approach to detecting and classifying emotions and attitudes expressed in textual data (Liu, 2015). Sentiment analysis enables the systematic quantification of subjective information in large text corpora, allowing us to assess the prevalence and distribution of different emotional expressions. Given the volume of data in our study, sentiment analysis provides a scalable method for identifying patterns in emotional responses to news content.

Sentiment analysis works by matching words or entire sentences in a text to predefined dictionaries or thesauri that classify terms based on emotions or positive and negative sentiment. These dictionaries contain words that have been assigned sentiment categories in advance.

All sentiment analyses were conducted in R, a widely used statistical computing language known for its powerful text analysis capabilities. R offers a comprehensive suite of libraries for natural language processing and sentiment analysis, allowing for flexible and reproducible research workflows. In this study, we employed multiple sentiment analysis techniques to ensure robust and comparative insights into emotional expressions. The following two approaches were used:

(1) The **NRC Emotion-Based Sentiment Analysis** (Mohammad et al., 2013) was implemented using the NRC Emotion Lexicon, a pre-annotated dictionary that categorizes words into eight basic emotions (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust) as well as positive and negative sentiment categories. This method assigns emotional labels to words in the dataset and provides an aggregate count of words associated with each emotion, allowing for a fine-grained breakdown of the emotional spectrum present in the text.

Sentiment	**Words**	**Percent**
negative	3.316	23,9%
fear	1.474	10,6%
sadness	1.187	8,6%
anger	1.245	9,0%
disgust	1.056	7,6%
positive	2.308	16,6%
trust	1.230	8,9%
anticipation	837	6,0%
joy	687	5,0%
surprise	532	3,8%
Total	**13.872**	**100%**

Figure 1 – Number of words per sentiment in the NRC sentiment lexicon

Figure 1 describes the distribution of words in the NRC Sentiment Lexicon, categorizing them based on sentiment[1]. Overall, there are more negative than positive words in the lexicon. Among the negative sentiments, *fear* is the most common category, followed by *sadness*, *anger*, and *disgust*. On the positive side, *trust* is the most frequently represented category, followed by *anticipation*, *joy*, and *surprise*. Words associated with *fear* include *terror*, *danger*, and *afraid*. The *sadness* category contains words such as *grief*, *loss*, and *melancholy*. Words linked to *anger* include *rage*, *furious*, and *hostile*, while *disgust* is represented by terms like *repulsive*, *nauseating*, and *detestable*. For positive sentiments, *trust* includes words like *reliable*, *honest*, and *secure*. The *anticipation* category features words such as *expectation*, *hopeful*, and *eager*. Words related to *joy* include *happiness*, *delight*, and *cheerful*, while *surprise* encompasses terms like *astonished*, *amazed*, and *unexpected*.

The unequal distribution of words across sentiments in the NRC Sentiment Lexicon is likely due to linguistic, psychological, and methodological factors. Some emotions, like *fear* and *anger*, have more linguistic variations because they are evolutionarily significant and frequently expressed in human communication. In contrast, emotions like *disgust* and *surprise* may have fewer distinct terms since they are often more binary or short-lived. Additionally, *trust* has more associated words than *surprise*, possibly because it represents a stable, socially crucial emotion rather than a fleeting reaction. The lexicon was created through crowdsourcing, meaning the distribution also reflects how people perceive and associate words with emotions. Research suggests that languages develop richer vocabularies for emotions that are more relevant to survival, social interactions, or nuanced expression, which likely explains why certain categories contain more words than others (Cowen and Keltner, 2017).

(2) The **Context-Aware Sentiment Analysis** (in the following tables called “context sentiment”) was conducted using the sentiment library of R. This approach provides a sentence-level sentiment score that accounts for valence shifters such as negation, intensifiers, and adversative conjunctions, refining the overall sentiment polarity. Unlike simple lexicon-based methods, this approach enhances accuracy by considering the context in which words appear, producing an average sentiment score per text unit (e.g., sentence, paragraph, or document) for a more nuanced sentiment assessment. The output is a sentiment score, which represents the mean sentiment score for a given text unit. This score is calculated by aggregating individual word and phrase-level sentiment values while incorporating contextual modifiers. Positive values indicate overall positive sentiment, negative values indicate negative sentiment, and values close to zero suggest neutrality or a balance between positive and negative expressions.

[1] Source: https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm, last accessed 2025/02/06.

Several other sentiment analysis methods exist, including the Syuzhet approach and the AFINN lexicon-based method, both of which provide alternative sentiment scores. However, the Context-Aware Sentiment Analysis was chosen as the most suitable approach for this study. Unlike purely lexicon-based methods, it accounts for valence shifters such as negation, intensifiers, and adversative conjunctions, refining sentiment polarity at the sentence level. This makes it particularly effective for capturing the nuanced sentiment of user-generated content, where context significantly influences meaning.

3. Database

The dataset for the sentiment analysis consists of Daily Mail user comments, specifically a random sample of 150,000 randomly selected comments linked to 60,908 Daily Mail Online articles, all from the year 2021 (see also D4.2).

We can assume that user comments on news platform articles represent a valuable data source for analyzing and identifying users' opinions, attitudes, and emotional dispositions (Kubin et al., 2024). In the construction of the Daily Mail dataset a Python-based web scraping tool was developed to systematically extract data from the publication's online platform. The data collection targeted articles published in 2021. At the time of data collection, it was initially planned to extend the dataset of Daily Mail user comments to include those from the 2023/2024 period for the final analysis. Unfortunately, due to changes on the Daily Mail's website, it was no longer possible to extract this data, though the exact reasons for this restriction remain unknown to us. As a result, the following analyses will be conducted using the 2021 dataset. We do not anticipate that this limitation poses a significant issue for the study. While certain focal points or aspects may have shifted over time, the core relevance of the topics under investigation remains unchanged. Furthermore, we assume that the emotions expressed in the user comments, as well as the moral violations addressed in these discussions, are temporally stable. Therefore, the analyses based on the 2021 data should still hold validity in answering our research questions. The Daily Mail website serves as a platform where individuals with a wide range of opinions, including both moderate, conservative, and non-extreme views, as well as more radicalized, extreme perspectives, are represented. This is true regardless of the level of content moderation implemented by the platform. Importantly, the site attracts a significant demographic of middle-aged individuals, which aligns with the target population our study aims to address. This further reinforces the value of the dataset, as it provides insight into the discussions and sentiments of this critical group.

The dataset includes a comprehensive set of metadata for each article, such as a unique identifier (article ID), the headline, publication date, topic category as classified by the website, and the total number of user interactions in the form of comments. To capture audience engagement, the scraper was designed to retrieve the most recent comments up to a predetermined limit per article, ensuring consistent data structure for analysis. For each comment, the dataset records relevant details to provide insight into user interaction and engagement. These include the comment text, a user ID, the comment's timestamp (creation date), and the article's topic category (news, sports, debate etc.).

Initially, 225,265 articles with comments were retrieved. After data cleansing, which involved restricting the dataset to 2021 articles and removing duplicates, a total of 224,981 articles remained as raw data. At the time of download in March 2023, 60,161,527 comments were associated with these articles, of which 41,797,198, or 69.5%, were successfully downloaded. Due to the technical challenges of accessing data from the Daily Mail's online system and the specific methods employed in data retrieval, we obtained a large but partial dataset, representing 69.5% of the total comments linked to the selected articles. This subset primarily contains the most recent comments, reflecting the limitations encountered in the data collection process.

From the complete dataset of Daily Mail comments, we extracted a random sample of 150,000 user comments. This sample size is deemed sufficiently large to capture the breadth of topics, sentiments, and moral foundations that we aim to investigate. At the same time, 150,000 comments remain a manageable quantity for the Natural Language Processing (NLP) methods we intend to use for measuring emotions and identifying the relevant moral foundations. This balance between breadth of content and computational feasibility makes the sample appropriate for our analytical objectives.

4. Results

4.1. Overall Sentiment Distribution in Daily Mail User Comments

Sentiment	Words	Percent
Negative	249.311	16,7%
Fear	138.162	9,2%
Sadness	120.611	8,1%
Anger	111.595	7,5%
Disgust	80.412	5,4%
Positive	282.116	18,8%
Trust	182.846	12,2%
Anticipation	146.206	9,8%
Joy	112.022	7,5%
Surprise	73.480	4,9%
Total	**1.496.761**	**100%**

Figure 2 – Overall Sentiment Distribution in 150,000 Daily Mail User Comments (2021)

Figure 2 presents the distribution of classified words in Daily Mail user comments across different sentiments. It is important to note that multiple assignments are possible, meaning a single word can be associated with multiple sentiments. The table displays the number of words per sentiment and their percentage of all assigned words, accounting for these overlaps. The distribution closely mirrors that of the NRC Sentiment Lexicon, with one key exception: while the NRC Sentiment Lexicon contains slightly more negative than positive words overall, the Daily Mail user comments exhibit the opposite pattern, with a slightly higher proportion of positive words. This does not mean, however, that positive sentiments dominate in the user comments.

When analyzing the overall sentiment score, a different pattern emerges. Overall, comments with a negative sentiment score slightly outweigh those with a positive sentiment score. 52% of the comments have a negative sentiment score, while 48% have a positive sentiment score. **The overall average Context-Aware Sentiment Score is -0.017**. That indicates a slight tendency toward negative sentiment across all comments. This highlights a key distinction between word-count-based and context-aware sentiment analysis. While the NRC method counts positive and negative words, it does not account for context, negation, or intensification, which can significantly alter the overall sentiment. Positive words often appear in critical or negative contexts, diminishing their impact, while negative words tend to carry stronger emotional intensity, pulling the sentiment score downward. Additionally, contrastive sentence structures can lead to mixed sentiments, where negative expressions dominate despite the presence of positive words. Online news comments frequently lean toward criticism and dissatisfaction, further reinforcing the slightly negative overall sentiment and highlighting the importance of context-aware sentiment analysis over simple word frequency counts (Kubin et al., 2024).

Therefore, across all comments, there is a slightly negative sentiment, with significant differences emerging when analyzing various article categories, topics, and their connection to moral framing.

To illustrate positive and negative sentiments, we provide examples from the text corpus. The three comments selected as the most negative in terms of context sentiment score exemplify highly negative sentiment due to their strong language, emotional intensity, and critical tone.

Highly negative comments

The first comment responds to the article "Tony Blair sets out his OWN lockdown exit strategy as he calls for traffic light scheme for easing rules, localised crackdowns on Covid outbreaks and a full Treasury analysis of the cost of the roadmap." A user writes: *"A despicable, vile, odious, contemptible, deplorable, slimy, wretched, abhorrent, detestable, pitiable, abominable, foul, obnoxious, loathsome, reptilian, repulsive, squalid, disgusting, cowardly, pathetic, unsavory, horrid, revolting creature, with no vaccine to protect us against him, GO AWAY!"* This comment stands out due to the sheer density of extremely negative adjectives, creating a highly emotional, hostile, and degrading tone toward Blair. The long list of pejorative descriptors intensifies the strongly negative sentiment, contributing to the extremely low sentiment score. The comment seems as if it was written specifically to serve as an exceptionally strong example of negative sentiment.

The second comment follows the article "Why gaffes - and an unhealthy, ageing nation - are to blame: BEN SPENCER analyses why Britain's Covid-19 death toll is so high." The comment reads: *"Yes, obesity is a real problem as an underlying condition, but perhaps an even bigger problem is that it is highly politically incorrect and considered discriminatory and even an actionable offense to say someone is fat!"* While not as emotionally charged as the first, this comment expresses frustration and criticism, particularly toward societal attitudes on political correctness. The claim that discussing obesity is "considered discriminatory and even an actionable offense" suggests sarcasm and dissatisfaction, reinforcing a negative sentiment.

The third comment appears under the article "Trump tells Florida rally that NY prosecutors are behaving like third world DICTATORS in pursuing a 'political vendetta' against him - and says the 'fabricated charges' will only make him stronger." The user states: *"TDS is a very dangerous incurable disease and affects the whole world it's truly terrifying to witness a Country destroy itself from within, the rage over the personality of one man tips so many into insanity ....bizarre."* This comment conveys alarm, hostility, and frustration, referring to "Trump Derangement Syndrome" (TDS) as "a very dangerous incurable disease" and describing the political situation as "truly terrifying" and a sign of the country destroying itself from within." The strong, dramatic language contributes to its highly negative sentiment score.

Highly positive comments

The following comments exemplify highly positive sentiment based on their strongly affirmative language and emotional intensity. The first comment appears under the article "Pro rugby players see their brain function deteriorate after just ONE season, study claims - and scientists warn tackles, not just concussions, are to blame." The user states: *"The amateur game has less skill and power, but was more entertaining - people play for the love of it is preferable, and offers a better way ahead for the sport."* This comment conveys a positive and nostalgic perspective on amateur rugby, highlighting appreciation and preference for the game in its less commercialized form.

The second comment follows the article "Bomb squad carry out controlled explosion close to house raided in Poppy Day blast probe as UK terror threat is raised to severe and it emerges 'suicide bomber was from Middle East and UNKNOWN to MI5'." The user writes: *"Now that's a real hero, wow what a brave selfless man and what great thinking and well observed, this man has saved many lives I'm sure, and yes he deserves a top medal for bravery, quick thinking and selflessness, well done indeed buddy."* This comment is overwhelmingly positive, filled with praise, admiration, and gratitude for the individual involved. The use of words like "hero," "brave," "selfless," "great thinking," and "well done" reinforces its highly positive sentiment.

The third comment appears under the article "The parallels are striking - a stunning Californian who fell for an aristocrat. Here, she says: I'm an African American who married into the British upper-class and made it work. It's sad Meghan couldn't, too." The user writes: *"What a lovely strong woman that is easy to admire, humble, respectful and accepting of people and in turn gets respected and accepted by others."* This comment is clearly purely positive, expressing admiration for the woman featured in the article.

4.2. Sentiment Variation across Article Categories

We now analyze the sentiment differences across various article categories on Daily Mail Online, examining how sentiment varies depending on the type of content. We consider only the categories with at least 100 comments: The **News** section covers current events, politics, and global affairs, often focusing on serious and sometimes controversial topics. **TV & Showbiz** features entertainment news, celebrity gossip, and updates on television, film, and music industries. The **Femail** (sic!) section includes articles on lifestyle, fashion, relationships, and women's interests. **Sport** provides coverage of major sporting events, match results, and athlete news. The **Debate** category presents opinion pieces and reader discussions on political, social, and cultural issues. **Health** focuses on medical advancements, fitness, well-being, and public health topics. This also includes content related to the COVID-19 pandemic. **Money** includes financial news, economic trends, personal finance advice, and investment insights. **Science & Tech** reports on technological developments, scientific discoveries, and innovations across various fields. **Travel** features destination guides, travel tips, and vacation recommendations, often highlighting leisure and adventure themes. **Home** covers interior design, home improvement, and lifestyle-related domestic topics, while **Property** focuses on real estate trends, market insights, and housing-related content. By examining sentiment across these diverse categories, we can better understand how different types of news and discussions shape the emotional tone of user comments.

Figure 3 illustrates the distribution of sentiment across different content categories on the *Daily Mail* website, specifically analyzing how sentiment in user comments varies depending on the type of content. The first table presents the absolute number of words per sentiment, indicating, for example, that in the comments on *Health* articles, a total of 1,966 words were classified as expressing *Anger*. The rightmost column displays the total word count across all comments within each category.

Absolute numbers

Category	Anger	Fear	Sadness	Disgust	Anticipati	Joy	Trust	Surprise	Negative	Positive	Context sent.	Words
Health	1.966	3.303	2.674	1.702	2.612	1.637	3.168	1.281	5.382	5.312	-0,039	119.844
News	78.617	100.445	82.770	54.390	94.239	67.871	121.598	48.574	174.314	184.104	-0,031	4.023.384
Debate	3.965	4.753	4.310	2.800	4.911	3.628	6.463	2.303	8.995	10.220	-0,023	211.523
Property	61	96	99	51	126	107	131	44	187	255	0,001	5.590
Sciencetech	1.181	1.637	1.395	1.041	1.867	1.479	2.279	875	2.933	3.818	0,001	82.931
Tvshowbiz	10.669	11.998	12.731	9.694	17.550	16.708	19.853	8.592	24.103	32.158	0,013	666.380
Travel	80	108	101	55	175	167	189	83	211	341	0,020	6.852
Home	97	136	134	80	188	182	258	97	264	403	0,021	7.727
Femail	6.671	7.018	7.904	5.322	10.453	9.907	12.742	4.929	14.850	20.574	0,022	413.643
Money	1.429	1.770	1.589	783	2.815	2.158	3.243	1.237	3.459	4.979	0,023	101.562
Sport	6.782	6.821	6.811	4.450	11.166	8.108	12.820	5.412	14.458	19.784	0,026	393.231
Total	**111.518**	**138.085**	**120.518**	**80.368**	**146.102**	**111.952**	**182.744**	**73.427**	**249.156**	**281.948**	**0,003**	**6.032.667**

Per words

Category	Anger	Fear	Sadness	Disgust	Anticipati	Joy	Trust	Surprise	Negative	Positive	Context sent.	Words
Health	1,6%	2,8%	2,2%	1,4%	2,2%	1,4%	2,6%	1,1%	4,5%	4,4%	-0,039	119.844
News	2,0%	2,5%	2,1%	1,4%	2,3%	1,7%	3,0%	1,2%	4,3%	4,6%	-0,031	4.023.384
Debate	1,9%	2,2%	2,0%	1,3%	2,3%	1,7%	3,1%	1,1%	4,3%	4,8%	-0,023	211.523
Property	1,1%	1,7%	1,8%	0,9%	2,3%	1,9%	2,3%	0,8%	3,3%	4,6%	0,001	5.590
Sciencetech	1,4%	2,0%	1,7%	1,3%	2,3%	1,8%	2,7%	1,1%	3,5%	4,6%	0,001	82.931
Tvshowbiz	1,6%	1,8%	1,9%	1,5%	2,6%	2,5%	3,0%	1,3%	3,6%	4,8%	0,013	666.380
Travel	1,2%	1,6%	1,5%	0,8%	2,6%	2,4%	2,8%	1,2%	3,1%	5,0%	0,020	6.852
Home	1,3%	1,8%	1,7%	1,0%	2,4%	2,4%	3,3%	1,3%	3,4%	5,2%	0,021	7.727
Femail	1,6%	1,7%	1,9%	1,3%	2,5%	2,4%	3,1%	1,2%	3,6%	5,0%	0,022	413.643
Money	1,4%	1,7%	1,6%	0,8%	2,8%	2,1%	3,2%	1,2%	3,4%	4,9%	0,023	101.562
Sport	1,7%	1,7%	1,7%	1,1%	2,8%	2,1%	3,3%	1,4%	3,7%	5,0%	0,026	393.231
Total	**1,8%**	**2,3%**	**2,0%**	**1,3%**	**2,4%**	**1,9%**	**3,0%**	**1,2%**	**4,1%**	**4,7%**	**0,003**	**6.032.667**

Difference to total

Category	Anger	Fear	Sadness	Disgust	Anticipati	Joy	Trust	Surprise	Negative	Positive	Context sent.	Words
Health	-0,2%	0,5%	0,2%	0,1%	-0,2%	-0,5%	-0,4%	-0,1%	0,4%	-0,2%	-0,039	119.844
News	0,1%	0,2%	0,1%	0,0%	-0,1%	-0,2%	0,0%	0,0%	0,2%	-0,1%	-0,031	4.023.384
Debate	0,0%	0,0%	0,0%	0,0%	-0,1%	-0,1%	0,0%	-0,1%	0,1%	0,2%	-0,023	211.523
Property	-0,8%	-0,6%	-0,2%	-0,4%	-0,2%	0,1%	-0,7%	-0,4%	-0,8%	-0,1%	0,001	5.590
Sciencetech	-0,4%	-0,3%	-0,3%	-0,1%	-0,2%	-0,1%	-0,3%	-0,2%	-0,6%	-0,1%	0,001	82.931
Tvshowbiz	-0,2%	-0,5%	-0,1%	0,1%	0,2%	0,7%	-0,1%	0,1%	-0,5%	0,2%	0,013	666.380
Travel	-0,7%	-0,7%	-0,5%	-0,5%	0,1%	0,6%	-0,3%	0,0%	-1,1%	0,3%	0,020	6.852
Home	-0,6%	-0,5%	-0,3%	-0,3%	0,0%	0,5%	0,3%	0,0%	-0,7%	0,5%	0,021	7.727
Femail	-0,2%	-0,6%	-0,1%	0,0%	0,1%	0,5%	0,1%	0,0%	-0,5%	0,3%	0,022	413.643
Money	-0,4%	-0,5%	-0,4%	-0,6%	0,3%	0,3%	0,2%	0,0%	-0,7%	0,2%	0,023	101.562
Sport	-0,1%	-0,6%	-0,3%	-0,2%	0,4%	0,2%	0,2%	0,2%	-0,5%	0,4%	0,026	393.231
Total	**0,0%**	**0,0%**	**0,0%**	**0,0%**	**0,0%**	**0,0%**	**0,0%**	**0,0%**	**0,0%**	**0,0%**	**0,003**	**6.032.667**

Figure 3 – Sentiment distribution across Daily Mail article categories 2021, categories with 100 comments and more, N = 149,921 articles)

The second table provides relative percentages, showing the proportion of words associated with each sentiment within a given category, relative to the total number of words in that category's comments. For instance, 1.6% of all words in the *Health* category comments were assigned to the sentiment *Anger*. It is important to note that these percentage values appear low because the base includes all words in the comments, including stopwords such as articles (*e.g., "the"*) and conjunctions (*e.g., "and", "but"*).

The third table highlights which sentiments appear more or less frequently than expected in each content category. Green bars indicate that a sentiment is more prevalent than average, whereas red bars indicate that a sentiment is less prevalent than average. The values in this table are calculated by determining the difference between the relative percentage of a senti-ment in a specific category and its overall relative percentage across all comments. For example, in the case of *Anger* in the *Health* category, 1.6% of all words in Health comments are associated with *Anger*, whereas *Anger* accounts for 1.8% of all words across all comments. This results in a difference of -0.2 percentage points, indicating that *Anger* appears less frequently than average in *Health* comments.

4.2.1. Overall Sentiment

Examining the **average sentiment scores** across different content categories, we focus on the **Context-Sentiment** column on the far right of the table. The categories are sorted by sentiment score, with those at the top representing article categories where comments tend to be more negative, while those at the bottom contain comments with a more positive sentiment on average.

Three content categories stand out as having an overall negative sentiment in user comments: **Health, News, and Debate**. The Health category has the most negative sentiment score, which can likely be attributed to its coverage of serious and often distressing topics, such as illness, medical concerns, and public health crises. Additionally, this category includes articles related to the COVID-19 pandemic, a subject that has generated particularly polarizing discussions and emotionally charged reactions. Similarly, News exhibits an overall negative sentiment, likely due to the nature of news reporting, which frequently covers topics such as crime, politics, economic instability, and global conflicts—all of which elicit frustration, anger, or concern. The Debate category, as expected, also has a negative sentiment score. Given that it consists of opinion pieces and politically charged discussions, it naturally fosters strongly worded disagreements, criticism, and ideological conflicts, which contribute to its negative tone.

On the opposite end of the spectrum, the categories with the most positive sentiment scores in user comments are **Sport, Money, and Femail**. The Sport category tends to attract enthusiastic engagement, admiration for athletes, and celebratory discussions of victories, leading to a generally positive sentiment. The Money category produces more optimistic discussions, particularly when it covers topics such as investment opportunities, market growth, and financial success, which are often framed in a forward-looking and constructive manner. Meanwhile, the Femail category, which includes content on lifestyle, fashion, and human-interest stories, is more likely to elicit positive emotions, appreciation, and supportive interactions rather than controversy or negativity.

Other categories that also show consistently positive sentiment scores include **Home, Travel, TV, and Showbiz**. The Home section, which focuses on interior design, home improvement, and domestic lifestyle topics, generally fosters constructive and positive discussions rather than conflict. Similarly, the Travel section encourages excitement and the exchange of shared positive experiences, making it a category where comments often carry a highly positive tone. The TV & Showbiz category, covering entertainment, celebrity news, and pop culture, tends to spark lighthearted, engaging, and generally favorable discussions rather than strong criticism or negativity.

Two categories, **Property** and **Science & Tech**, exhibit a more neutral sentiment balance, with comments neither strongly positive nor negative on average. The Property section, which covers real estate trends and the housing market, is largely practical in nature, leading to discussions that are informative rather than emotionally charged. Meanwhile, Science & Tech articles likely seem to foster more rational discussions, as readers engage with technological advancements and scientific topics in a more objective and fact-driven manner.

This structured analysis reveals a clear (and not surprising) trend: categories dealing with controversial or distressing topics such as politics, debate, and also health tend to generate negative sentiment, while those centered on entertainment, lifestyle, and leisure foster a more positive emotional response in user comments.

4.2.2. Basic Emotions

Now, we turn to the basic sentiment categories, analyzing how specific emotions relate to different types of content (NRC sentiment values). First, we examine the three content categories with overall negative sentiment scores: **Health, News, and Debate**.

Looking at **Anger**, user comments in the **News** category show an above-average frequency of this sentiment. This suggests that news topics, particularly those covering politics, societal issues, and controversial events, often elicit frustration, outrage, or discontent from readers. In contrast, comments in the **Health** category are primarily associated with **Fear**, reflecting the nature of health-related discussions, which often involve concerns about illness and medical public health crises, i.e. the Covid-19 pandemic in many cases. To a lesser extent, **Fear** also appears above average in comments on **News** articles, indicating that certain news topics—such as crime, conflict, or economic instability—are perceived as threatening or unsettling.

Sadness is another sentiment that occurs above average in the **Health** category, likely due to the emotional weight of topics related to disease, suffering, and loss. Similarly, **Disgust** is more prevalent in Health-related discussions, which may be driven by reactions to medical failures, ethical concerns, or political measures. While the **News** category is dominated by **Fear** and **Anger**, the **Health** category has a **broader emotional spectrum**, with Fear, Sadness, and Disgust all playing a significant role. In the **Debate** category, no single sentiment is overwhelmingly dominant, but **Fear** appears slightly above average, likely reflecting uncertainty or apprehension over divisive political and social issues discussed in this section.

When analyzing content categories where user comments have an overall positive sentiment score, **Joy** emerges as the most dominant emotion. This suggests that user engagement with entertainment, lifestyle, and sports-related content is often driven by happiness, enthusiasm, and appreciation. Sport and Money articles, in particular, show a high frequency of (positive) **Anticipation**, which reflects the excitement of upcoming games, financial opportunities, or economic prospects. The Home category, on the other hand, is rather associated with **Trust**, suggesting that discussions in this section often revolve around shared experiences, advice, and a sense of reliability in domestic and lifestyle topics. Finally, **Surprise** appears above average primarily in **Sport**-related comments, likely due to the unpredictability of matches, unexpected victories, and dramatic moments in sports coverage.

The sentiments across content categories show that negative emotions—particularly fear, anger, and disgust—are prevalent in certain content categories such as health, news, and debate, making them more susceptible to sensationalized misinformation and conspiracy narratives. This suggests that, in addition to fact-checking and content moderation, reducing emotional intensity through transparent communication and contextualized reporting would be essential. However, this approach naturally conflicts with the business model of social media and news platforms, which thrive on emotionally engaging content. Conversely, content categories associated with positive emotions, such as sports and entertainment, foster less contentious discussions, highlighting the potential of messenger-driven and trust-based narratives to address polarizing and misinformation.

4.1. Sentiment Differences across Topics

Next, we analyze the relationship between sentiment and specific topics or keywords within the *Daily Mail* user comments. As outlined in Deliverable D4.2, our text analysis has identified 14 recurring themes that appear frequently in the user comments. The following sections will explore these topics, examining how sentiment varies across different themes and discussing the implications of these patterns. Here are the topics that have been found:

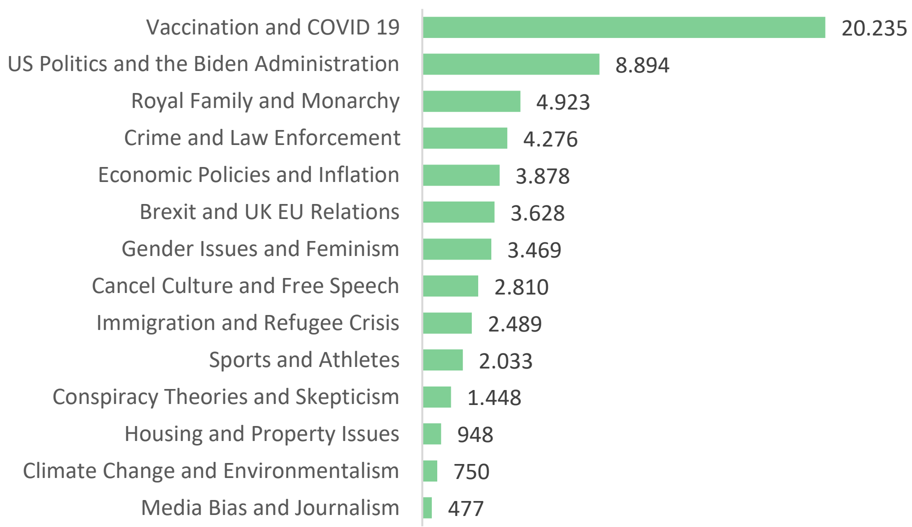

Figure 4 – Topics by number of Daily Mail user comments (2021, N = 52,717, multiple counts possible).

Figure 4 presents the most prominent topics in the Daily Mail user comments, ranked in descending order based on their frequency. The data clearly illustrate the extent to which the discourse in 2021 was dominated by the topic of COVID-19 and vaccination. From a random sample of 150,000 user comments, we identified a total of 52,717 topic assignments. Notably, 20,235 comments—more than 38% of the topic related comments—explicitly refer to vaccination and COVID-19, underscoring the topic's pervasive presence in user discussions. Beyond the pandemic, several other topics emerged as particularly prominent in the discourse. These include U.S. politics as well as discussions surrounding the British Royal Family and the monarchy. Additionally, crime-related news, as well as economic policy and inflation, were frequently debated subjects. It is important to note that the analysis allows for multiple topic assignments per comment, meaning that a single comment can be associated with more than one topic.

	Comments on topics		All comments		
Sentiment	**Words**	**Percent**	**Words**	**Percent**	**Saldo**
Negative	109.535	4,4%	249.311	4,1%	0,2%
Fear	64.154	2,6%	138.162	2,3%	0,3%
Sadness	53.319	2,1%	120.611	2,0%	0,1%
Anger	49.311	2,0%	111.595	1,8%	0,1%
Disgust	33.099	1,3%	80.412	1,3%	0,0%
Positive	117.802	4,7%	282.116	4,7%	0,0%
Trust	76.380	3,0%	182.846	3,0%	0,0%
Anticipation	57.137	2,3%	146.206	2,4%	-0,1%
Joy	41.573	1,7%	112.022	1,9%	-0,2%
Surprise	30.675	1,2%	73.480	1,2%	0,0%
Total (unique)	**2.513.648**	**100,0%**	**6.036.225**	**100%**	

Figure 5 – Comparison: Sentiments of comments on topics vs all comments.

Figure 5 presents the distribution of sentiments in user comments, comparing all comments with those specifically related to the identified topics. The data seem to indicate that these topics tend to be rather controversial or polarizing.

To facilitate comparison, we calculated the *Saldo* column, representing the difference between the proportion of a sentiment within topic-related comments and its overall occurrence across all comments. A positive difference (green bar) signifies overrepresentation, indicating that the sentiment appears more frequently in topic-related comments. Conversely, a negative difference (red bar) denotes underrepresentation, meaning the sentiment occurs less frequently in these comments. The findings reveal that negative sentiments are notably more prevalent in discussions surrounding the identified topics. In particular, emotions such as *fear*, overall *negative sentiment*, *sadness*, and *anger* are significantly overrepresented. In contrast, *joy* and *anticipation* appear less frequently in comments related to these topics than in the dataset as a whole. Interestingly, despite the predominance of negative sentiments, the *positive* category is also slightly over-represented in topic-related discussions. This suggests that comments addressing the topics exhibit a slightly higher overall emotional intensity compared to the user comments in general.

As described in the context of the text analysis in D4.2, we defined keywords corresponding to 14 specific topics and subsequently categorized user comments based on the presence of these keywords. This classification now serves as the foundation for analyzing the relationship between comments containing specific keywords and the associated emotions. Figure 6 illustrates a network graph representing the relationships between specific sentiments and keywords found in the user comments. Only keywords that appear in at least 100 comments are depicted (64 out of 86). An arrow pointing from a keyword to a sentiment indicates that this association occurs with above-average frequency. Importantly, this visualization does not depict the absolute strength of connections but rather highlights typical patterns, showing which emotions are disproportionately linked to certain keywords in user discussions.

The structure of the network further enhances pattern recognition, as nodes with stronger relationships are positioned closer together, while those with weaker connections are farther apart. An important feature of the visualization is the clear division into two halves: negative emotions dominate the left side, while positive emotions are concentrated on the right. This organization makes it readily apparent which keywords are most strongly associated with each sentiment.

On the left side of the network, **anger** and **sadness** appear closely related, indicating that they frequently co-occur with the same keywords. In network analysis terms, these sentiments are structurally equivalent, meaning they share similar relational patterns (Borgatti and Grosser, 2015). Keywords such as prison, crime, and pandemic are particularly associated with both anger and sadness. Additionally, the figure reveals the emotional intensity of discussions surrounding the British monarchy, as names like Harry and Meghan are also disproportionately linked to anger and sadness.

Below these, the sentiments **fear** and **disgust** form another structurally equivalent pair, frequently co-occurring with keywords such as climate change, conspiracy, and COVID-19. The placement of COVID-19 in this network is particularly insightful. While COVID-related comments constitute more than 38% of all user comments, their connection to fear does not appear exceptionally strong in the visualization. This is because the network highlights above-average associations rather than overall frequency. Nevertheless, it remains clear that fear is the dominant sentiment associated with COVID-19.

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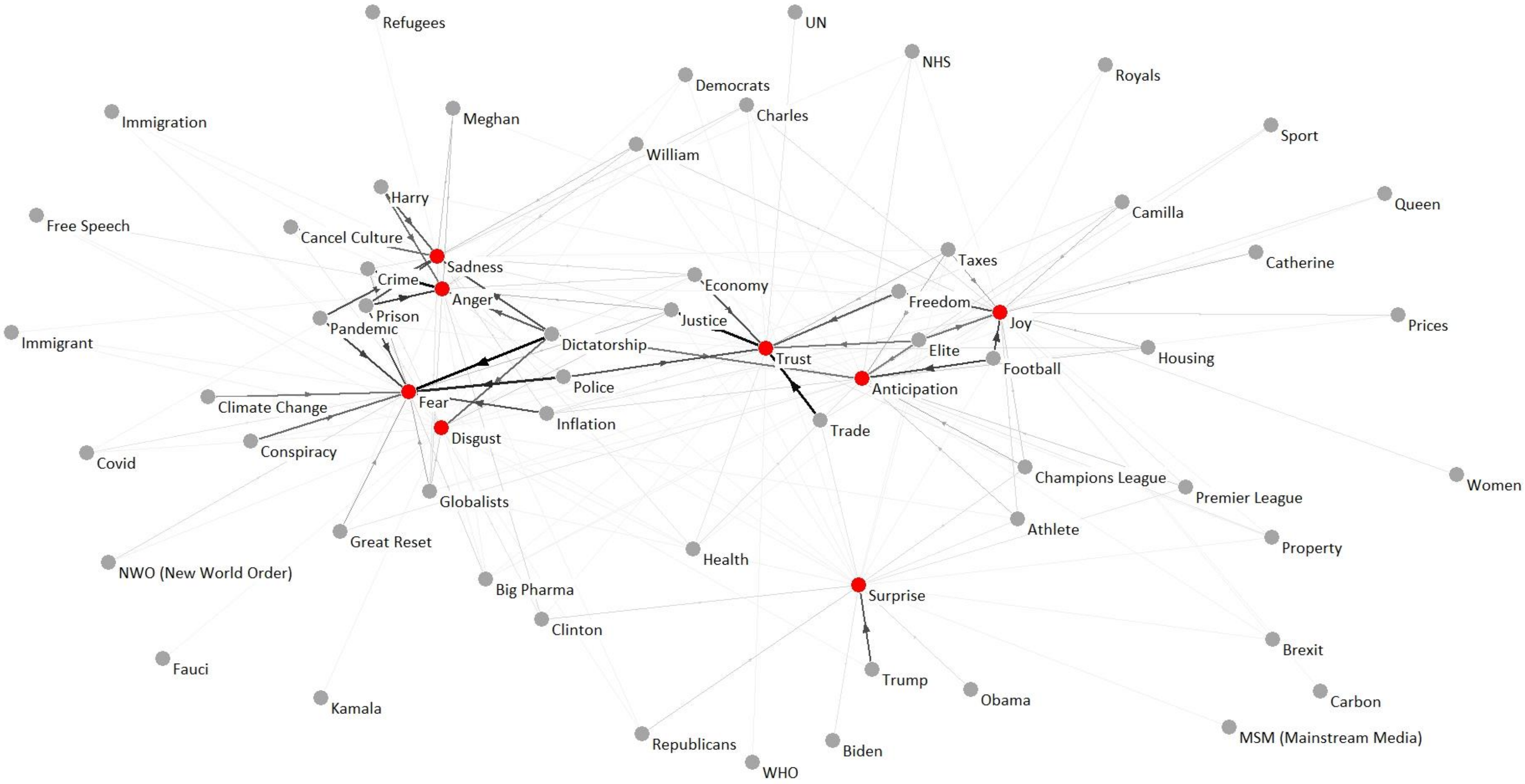

Figure 6 – Network of relations between keywords and sentiments (N = 52,717 Daily Mail user comments).

On the right side of the network, positive sentiments such as trust, anticipation, and joy are clustered together. In many cases, their associations with specific keywords are intuitive. For example, sports-related terms such as football, Champions League, athlete, and Premier League are strongly linked to joy. However, some connections are less immediately interpretable without a closer examination of the user comments. One such example is the association between taxes and joy, which might initially seem counterintuitive. This suggests that comments containing the keyword *taxes* appear in a predominantly positive context, whether related to low taxes or another generally favorable theme. Another noteworthy observation is the placement of Brexit on the right side of the network, where it is associated with positive sentiments. This suggests that, within this dataset, Brexit discussions were more often framed in a positive emotional context. Additionally, the strong connection between Trump and surprise stands out, indicating that in 2021 discussions about the former U.S. president frequently elicited unexpected or unpredictable reactions (as they do today).

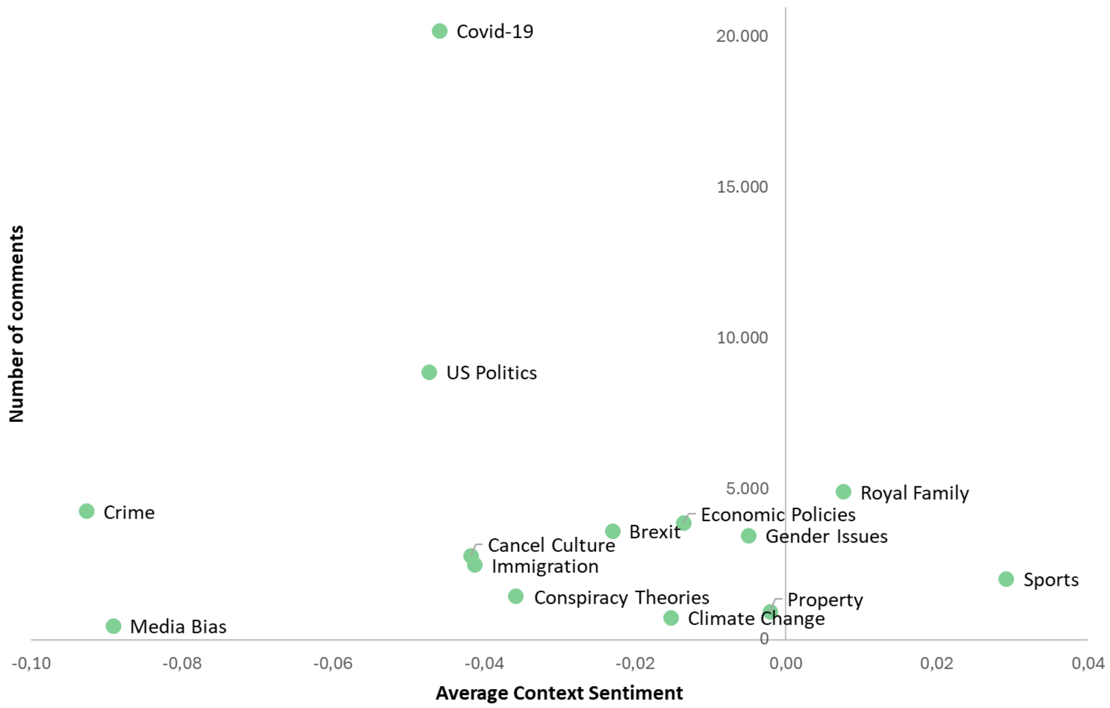

Figure 7 – Topics by number of comments and average context sentiment (N = 52,727 Daily Mail comments, 2021).

The relationship between themes and emotions becomes clearer when we analyze the 14 key topics that have emerged as particularly dominant in Daily Mail user comments. These topics represent the most frequently discussed and debated issues within the dataset. Figure 7 visualizes this relationship by mapping the topics on a two-dimensional plane. The **Y-axis** represents the total number of comments associated with each topic, thereby indicating the relative level of engagement and discussion surrounding each issue. The **X-axis**, on the other hand, represents the **Average Context Sentiment**, which quantifies whether the comments on a given topic tend to be more positive or more negative on average.

The vertical axis, where the value is set to zero, serves as a neutral threshold. Topics that cluster near this axis can be considered to have a more balanced sentiment distribution, meaning that, on average, they do not evoke particularly strong positive or negative emotions. Moving **to the right** along the X-axis, topics are increasingly associated with **positive sentiment**, indicating that user comments on these topics tend to be more approving, optimistic, or supportive. Conversely, topics positioned **to the left** of the Y-axis are associated with **negative sentiment**, meaning that the discourse surrounding these issues is generally critical, skeptical, or emotionally charged in a negative manner.

On average, the majority of topics tend to be associated with negative sentiment. This suggests that much of the discourse within the dataset is critical in nature and that users predominantly engage in discussions that reflect dissatisfaction, skepticism, or concern rather than optimism or approval. However, there are two exceptions. The topics **Sports** and **the Royal Family** are positioned on the positive side of the sentiment scale, indicating that comments referring to these subjects are, on average, more approving and favorable. Among the topics that exhibit an average negative sentiment, two stand out in particular: **Crime** and (perceived) **Media Bias**. The latter refers to user perceptions that media coverage is biased, distorted, or agenda-driven, which appears to be a highly contentious issue among commenters. These two topics display the strongest negative sentiment scores, suggesting that discussions surrounding them are highly critical and emotionally charged. **COVID-19**, as we have already noted, is by far the most-discussed topic in the dataset. It generates the highest number of user comments, indicating that it was a major focus of discussion. While COVID-19 is firmly located on the negative sentiment side of the spectrum, its sentiment is not as negative as that of **Crime** and **Media Bias**. This suggests that while the topic was largely discussed in a negative manner, it also elicited a wider range of opinions compared to the most strongly negative topics.

Can we determine, based on the data, how polarized the discussions associated with these topics are? In other words, do these topics tend to generate uniform opinions, where the sentiment is largely one-sided, or are they characterized by deeply divided opinions, indicating strong polarization? Sentiment analysis alone is not an ideal instrument for directly measuring polarization, as true polarization would require a more explicit assessment of agreement versus disagreement. However, sentiment distribution can serve as an **initial indicator** of polarization by highlighting the extent to which both positive and negative sentiments coexist within discussions on a given topic.

	Average Context Sentiment				
Topic	Negative	Neutral	Positive	Total	Sort
Vaccination and COVID 19	9.725	4.519	5.991	20.235	1
US Politics and the Biden Administration	4.279	2.027	2.588	8.894	2
Royal Family and Monarchy	1.862	1.093	1.968	4.923	3
Crime and Law Enforcement	2.484	812	980	4.276	4
Economic Policies and Inflation	1.568	911	1.399	3.878	5
Brexit and UK EU Relations	1.503	908	1.217	3.628	6
Gender Issues and Feminism	1.399	748	1.322	3.469	7
Cancel Culture and Free Speech	1.340	576	894	2.810	8
Immigration and Refugee Crisis	1.145	587	757	2.489	9
Sports and Athletes	677	443	913	2.033	10
Conspiracy Theories and Skepticism	682	306	460	1.448	11
Housing and Property Issues	375	215	358	948	12
Climate Change and Environmentalism	292	198	260	750	13
Media Bias and Journalism	287	85	105	477	14

Topic	Negative	Neutral	Positive	Total	Sort
Vaccination and COVID 19	48%	22%	30%	100%	1
US Politics and the Biden Administration	48%	23%	29%	100%	2
Royal Family and Monarchy	38%	22%	40%	100%	3
Crime and Law Enforcement	58%	19%	23%	100%	4
Economic Policies and Inflation	40%	23%	36%	100%	5
Brexit and UK EU Relations	41%	25%	34%	100%	6
Gender Issues and Feminism	40%	22%	38%	100%	7
Cancel Culture and Free Speech	48%	20%	32%	100%	8
Immigration and Refugee Crisis	46%	24%	30%	100%	9
Sports and Athletes	33%	22%	45%	100%	10
Conspiracy Theories and Skepticism	47%	21%	32%	100%	11
Housing and Property Issues	40%	23%	38%	100%	12
Climate Change and Environmentalism	39%	26%	35%	100%	13
Media Bias and Journalism	60%	18%	22%	100%	14

Figure 8 – Distribution of negative, neutral, and positive comments across topics (N = 52,727 Daily Mail comments, 2021).

This issue is further explored in Figure 8, which presents a more detailed breakdown of sentiment distribution across the 14 topics. This figure ranks the topics based on the total number of comments and categorizes sentiment into three distinct groups: **negative, neutral, and positive**. To classify the sentiment scores, a threshold-based system is used. Topics with an Average Context Sentiment of less than -0.05 are categorized as negative, while those with an Average Context Sentiment greater than 0.05 are considered positive. All topics falling between these two thresholds are classified as neutral.

Figure 8 consists of two complementary tables. The first table presents the absolute number of comments within each sentiment category, providing a direct count of how many comments were classified as negative, neutral, or positive for each topic. The second table normalizes this information by displaying the **relative percentages** of each sentiment category within each topic.

One of the most immediate findings from Figure 8 is that, for nearly every topic, sentiment distribution is relatively balanced across the three categories. This suggests that most topics in the dataset are rather controversial or polarizing, as they provoke divided opinions rather than overwhelming consensus. The fact that both negative and positive sentiments appear in significant proportions across most topics indicates that these discussions are not merely driven by uniform approval or disapproval but rather by contentious debate and disagreement among users. However, a few notable exceptions emerge where sentiment distribution is more heavily skewed in one direction. The topic Media Bias and Journalism exhibits a 60% negative sentiment, indicating that users perceive media representation to be predominantly problematic, misleading, or biased. Similarly, Crime and Law Enforcement also exhibits a strong negative sentiment bias (58%), suggesting that discussions surrounding these issues are predominantly critical. Despite these exceptions, the overall sentiment distribution across most topics is remarkably even, reinforcing the idea that the topics under discussion are rather polarizing or at the very least controversial. The dataset does not reflect discussions that are characterized by broad consensus or uniformity of opinion. Instead, it presents a landscape where most topics generate divisive debates, with significant representation of both positive and negative sentiments, underscoring their inherently contentious nature.

Figure 9 illustrates the **relationship between sentiments and specific discussion topics**. It provides a structured overview of how different emotional expressions, as determined by the NRC Dictionary Approach, are distributed across 14 key topics. The figure consists of three distinct tables, each offering a different perspective on the interaction between sentiment and topic.

The first table presents the absolute number of comments. This means that for each topic, it lists the total number of comments that have been assigned a particular sentiment. Each comment is classified based on its emotional tone, whether positive, negative, or associated with a specific sentiment category such as anger, fear, disgust, sadness, anticipation, trust, joy, or surprise. The final column on the right, labeled Context Sentiment Score, represents the average sentiment score for each topic. This score provides a general indication of whether a topic is predominantly associated with positive or negative sentiment. Since this table is based on absolute numbers, it reflects the raw frequency of comments related to a given topic and sentiment.

The second table moves beyond absolute frequencies and presents the relative proportions of sentiment within each topic. Instead of counting the total number of sentiment-labeled comments, this table normalizes the values by calculating the percentage of comments that fall into each sentiment category for a given topic. This is done by dividing the number of comments associated with a particular sentiment by the total number of comments for that topic. The result allows for a clearer understanding of which sentiments are most dominant within each topic in relative terms, providing a more nuanced picture than the first table.

Absolute number of comments

Topic	Commts.	Positive	Negative	Anger	Fear	Disgust	Sadness	Anticip.	Trust	Joy	Surprise	Cont. Sent.
Brexit and UK EU Relations	3.628	7.910	7.156	2.992	3.457	2.121	3.311	3.956	5.340	2.878	2.123	-0,02
Cancel Culture and Free Speech	2.810	6.130	5.991	2.661	3.120	1.897	2.755	2.682	3.767	2.096	1.288	-0,04
Climate Change and Environmentalism	750	1.747	1.521	623	1.234	490	647	773	1.109	659	383	-0,02
Conspiracy Theories and Skepticism	1.448	3.866	3.484	1.402	2.468	1.041	1.468	2.089	2.714	1.495	833	-0,04
Crime and Law Enforcement	4.276	12.325	11.628	7.000	10.165	3.300	5.375	4.735	9.845	3.012	2.417	-0,09
Economic Policies and Inflation	3.878	10.509	8.917	3.726	4.686	2.288	4.168	5.510	8.261	4.464	2.592	-0,01
Gender Issues and Feminism	3.469	7.930	6.455	3.001	3.725	2.381	3.223	3.923	4.974	3.504	1.753	0,00
Housing and Property Issues	948	2.580	2.005	962	1.194	547	1.007	1.388	1.676	1.029	598	0,00
Immigration and Refugee Crisis	2.489	5.219	5.386	2.482	3.219	1.680	2.566	2.659	3.368	1.882	1.320	-0,04
Media Bias and Journalism	477	968	1.201	445	562	313	427	470	638	258	288	-0,09
Royal Family and Monarchy	4.923	11.787	10.807	6.439	4.076	3.056	6.818	5.719	7.264	4.865	2.604	0,01
Sports and Athletes	2.033	6.507	3.561	1.715	1.829	1.229	1.675	3.854	3.176	3.175	1.289	0,03
US Politics and the Biden Amin.	8.894	17.007	18.098	8.694	10.159	6.094	8.428	8.261	12.324	5.897	9.093	-0,05
Vaccination and COVID 19	20.235	45.354	45.132	16.892	27.513	12.917	21.709	21.678	27.257	13.475	10.225	-0,05

Words per comment

Topic	Commts.	Positive	Negative	Anger	Fear	Disgust	Sadness	Anticip.	Trust	Joy	Surprise	Cont. Sent.
Brexit and UK EU Relations	3.628	2,18	1,97	0,82	0,95	0,58	0,91	1,09	1,47	0,79	0,59	-0,02
Cancel Culture and Free Speech	2.810	2,18	2,13	0,95	1,11	0,68	0,98	0,95	1,34	0,75	0,46	-0,04
Climate Change and Environmentalism	750	2,33	2,03	0,83	1,65	0,65	0,86	1,03	1,48	0,88	0,51	-0,02
Conspiracy Theories and Skepticism	1.448	2,67	2,41	0,97	1,70	0,72	1,01	1,44	1,87	1,03	0,58	-0,04
Crime and Law Enforcement	4.276	2,88	2,72	1,64	2,38	0,77	1,26	1,11	2,30	0,70	0,57	-0,09
Economic Policies and Inflation	3.878	2,71	2,30	0,96	1,21	0,59	1,07	1,42	2,13	1,15	0,67	-0,01
Gender Issues and Feminism	3.469	2,29	1,86	0,87	1,07	0,69	0,93	1,13	1,43	1,01	0,51	0,00
Housing and Property Issues	948	2,72	2,11	1,01	1,26	0,58	1,06	1,46	1,77	1,09	0,63	0,00
Immigration and Refugee Crisis	2.489	2,10	2,16	1,00	1,29	0,67	1,03	1,07	1,35	0,76	0,53	-0,04
Media Bias and Journalism	477	2,03	2,52	0,93	1,18	0,66	0,90	0,99	1,34	0,54	0,60	-0,09
Royal Family and Monarchy	4.923	2,39	2,20	1,31	0,83	0,62	1,38	1,16	1,48	0,99	0,53	0,01
Sports and Athletes	2.033	3,20	1,75	0,84	0,90	0,60	0,82	1,90	1,56	1,56	0,63	0,03
US Politics and the Biden Amin.	8.894	1,91	2,03	0,98	1,14	0,69	0,95	0,93	1,39	0,66	1,02	-0,05
Vaccination and COVID 19	20.235	2,24	2,23	0,83	1,36	0,64	1,07	1,07	1,35	0,67	0,51	-0,05
Average		2,42	2,17	1,00	1,29	0,65	1,02	1,20	1,59	0,90	0,59	-0,03

Difference to average

Topic	Commts.	Positive	Negative	Anger	Fear	Disgust	Sadness	Anticip.	Trust	Joy	Surprise	Cont. Sent.
Brexit and UK EU Relations	3.628	0,24	0,20	0,17	0,34	0,07	0,11	0,11	0,12	0,11	0,01	-0,02
Cancel Culture and Free Speech	2.810	0,24	0,04	0,05	0,18	0,02	0,04	0,24	0,25	0,15	0,14	-0,04
Climate Change and Environmentalism	750	0,09	0,15	0,17	0,36	0,00	0,16	0,17	0,11	0,02	0,08	-0,02
Conspiracy Theories and Skepticism	1.448	0,25	0,23	0,03	0,42	0,07	0,00	0,25	0,28	0,13	0,02	-0,04
Crime and Law Enforcement	4.276	0,47	0,55	0,64	1,09	0,12	0,24	0,09	0,71	0,19	0,03	-0,09
Economic Policies and Inflation	3.878	0,29	0,13	0,04	0,08	0,06	0,06	0,22	0,54	0,25	0,07	-0,01
Gender Issues and Feminism	3.469	0,13	0,31	0,13	0,21	0,03	0,09	0,07	0,16	0,11	0,09	0,00
Housing and Property Issues	948	0,30	0,06	0,02	0,03	0,08	0,04	0,27	0,18	0,19	0,04	0,00
Immigration and Refugee Crisis	2.489	0,32	0,01	0,00	0,01	0,02	0,01	0,13	0,24	0,14	0,06	-0,04
Media Bias and Journalism	477	0,39	0,34	0,06	0,11	0,00	0,12	0,21	0,25	0,36	0,01	-0,09
Royal Family and Monarchy	4.923	0,02	0,02	0,31	0,46	0,03	0,37	0,03	0,11	0,09	0,07	0,01
Sports and Athletes	2.033	0,78	0,42	0,15	0,39	0,05	0,19	0,70	0,03	0,66	0,04	0,03
US Politics and the Biden Amin.	8.894	0,50	0,14	0,02	0,15	0,03	0,07	0,27	0,20	0,24	0,43	-0,05
Vaccination and COVID 19	20.235	0,18	0,06	0,16	0,07	0,01	0,06	0,13	0,24	0,23	0,09	-0,05
Average		**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**-0,03**

Figure 9 – Distribution of sentiments across topics (NRC sentiment approach, N = 52,727 Daily Mail comments, 2021).

The third table highlights whether specific sentiments appear with above-average or below-average frequency within each topic. This table is derived by computing the difference between the values in the second table (relative sentiment proportions per topic) and the overall average sentiment distribution across all topics (found in the bottom row of the second table). This difference indicates whether a sentiment is overrepresented or underrepresented in the context of a specific topic compared to the dataset-wide average. Green bars signify that a particular sentiment appears above average for a given topic, meaning that the topic tends to evoke this sentiment more frequently than the general discussion. In contrast, light red (pink) bars indicate that a sentiment is underrepresented, meaning that it occurs less frequently in discussions on that topic compared to the dataset-wide norm. This visualization allows for an intuitive assessment of which emotions are particularly prevalent or notably absent in discussions on certain topics.

Examining the relationship between individual sentiments and discussion topics in greater depth reveals clear patterns in how different themes evoke specific emotional responses. As previously noted, only two topics exhibit an overall positive sentiment: **Sports and Athletes** and **Royal Family and Monarchy**. These topics stand in stark contrast to the rest, as all other themes are rather associated with negative sentiment. Among these, **Crime and Law Enforcement** and **Media Bias and Journalism** emerge as the most negatively charged topics, displaying the highest frequency of negative sentiment.

Interestingly, while **Crime and Law Enforcement** is overwhelmingly associated with negativity, it also receives a notable share of positive sentiment. This suggests that discussions on crime are highly emotionally charged but not uniformly negative. Instead, users express both concern and approval, possibly reflecting a divide between those who criticize crime rates or law enforcement actions and those who support crime prevention measures. Similarly, **Conspiracy Theories and Skepticism** shows a similar emotional pattern, where both positive and negative sentiment appear frequently, indicating that it is a particularly polarizing and emotionalizing topic.

Other topics that are also characterized by a strong negative sentiment dominance include **COVID-19 and Vaccination**. Given the widespread societal impact of the pandemic, it is unsurprising that discussions on this topic are often marked by frustration, distrust, and negativity, whether regarding government measures, vaccine policies, or public health strategies.

Breaking down the negative sentiment categories further, we observe distinct trends in how different emotions manifest across topics. The sentiment **anger** is particularly pronounced in discussions related to Crime and Law Enforcement. This is expected, as crime and legal enforcement naturally provoke strong emotional reactions, particularly when incidents of injustice or perceived failures in law enforcement occur. Interestingly, Royal Family and Monarchy is also strongly associated with anger. This may be attributed to controversial events, scandals, or debates about the (perceived) behavior of certain family members, which provoke divided opinions and heated discourse.

When analyzing **fear**, we find that Crime and Law Enforcement is, predictably, a dominant topic. Crime is inherently linked to public concerns about safety and security, making it a key driver of fear-related sentiment. Other topics that evoke fear include Conspiracy Theories and Skepticism, which often involve narratives about hidden threats, governmental control, or large-scale deception, thereby fueling fear-based discourse. Climate Change and Environmentalism also ranks high in fear expression, reflecting growing concerns over environmental crises, natural disasters, and the future of the planet. Additionally, COVID-19 and Vaccination are strongly linked to fear, as health crises and uncertainty surrounding public health measures often contribute to anxiety and apprehension.

The sentiment **disgust** appears above average in discussions on Crime and Law Enforcement, which aligns with the moral and ethical outrage often associated with violent crime or legal injustices. Additionally, Conspiracy Theories and Skepticism also exhibit high levels of disgust, possibly due to users expressing disdain toward perceived misinformation, deception, or controversial narratives.

Sadness is another emotion that follows a distinct pattern. It is particularly prevalent in discussions about the Royal Family and Monarchy, likely due to major events such as deaths, illnesses, or scandals involving members of the monarchy, which often elicit widespread public sympathy or mourning. Additionally, Crime and Law Enforcement also ranks high in sadness, as news about crime victims, legal injustices, or tragedies naturally evokes sorrow and emotional distress.

Turning to positive sentiments, the sentiment **anticipation** is strongly linked to Sports and Athletes. This is intuitive, as sports inherently involve excitement, competition, and speculation about future outcomes, making anticipation a defining emotional component of sports discourse. However, anticipation is also frequently expressed in discussions about Housing and Property Issues as well as Economic Policies and Inflation. This could reflect users' expectations regarding financial markets, real estate trends, or economic reforms, where speculation and future-oriented thinking play a major role.

The sentiment **trust** appears in somewhat unexpected contexts. While trust is naturally associated with positive discussions, it is also present in topics that evoke fear, such as Conspiracy Theories and Crime. This initially appears counterintuitive, but a plausible interpretation is that users express trust in certain figures, institutions, or policies in response to fear-inducing events. For example, trust may be directed toward law enforcement, government actions, or scientific expertise, particularly in discussions where these elements are seen as solutions to perceived threats. Economic Policies and Inflation also show a relatively high level of trust, which could indicate confidence in financial regulations, economic reforms, or leadership figures.

When considering **joy**, Sports and Athletes emerges as the dominant topic. This is expected, as sports victories, celebrations, and moments of athletic excellence frequently elicit joy and enthusiasm. Additionally, U.S. Politics and the Biden Administration appears above average in generating **surprise**, indicating that political developments, elections, or unexpected policy decisions frequently lead to emotionally charged discussions.

These findings reveal a clear pattern in how different topics elicit specific emotional responses. While certain subjects, such as sports and the monarchy, maintain a largely positive sentiment, most discussion topics in the dataset are dominated by negative sentiment, particularly crime, media bias, and conspiracy theories. The emotions associated with these discussions vary significantly, with anger and fear being dominant in crime-related discussions, disgust being prominent in conspiracy-related topics, and sadness appearing frequently in discussions about the royal family. Conversely, positive emotions such as anticipation and trust emerge in more speculative or solution-oriented discussions, such as those about economic policies and housing issues. The findings suggest that public discourse on major societal issues is highly emotional, often polarized, and deeply influenced by underlying concerns, uncertainties, and expectations. The emotional intensity of these discussions indicates that these topics are not merely debated in a detached manner but are deeply embedded in public sentiment, shaping perceptions and attitudes toward key social, political, and economic issues.

4.2. Sentiments and Moral Foundations

Before turning to the question of which sentiments are associated with specific moral frames, it is essential to first examine the prevalence of moral foundations in the Daily Mail user comments. Figure 10 presents an overview of the distribution of moral foundations, ranked according to the number of comments in which they appear. This allows us to assess which moral values are most frequently referenced by users, as well as which violations of these values are particularly emphasized in public discourse.

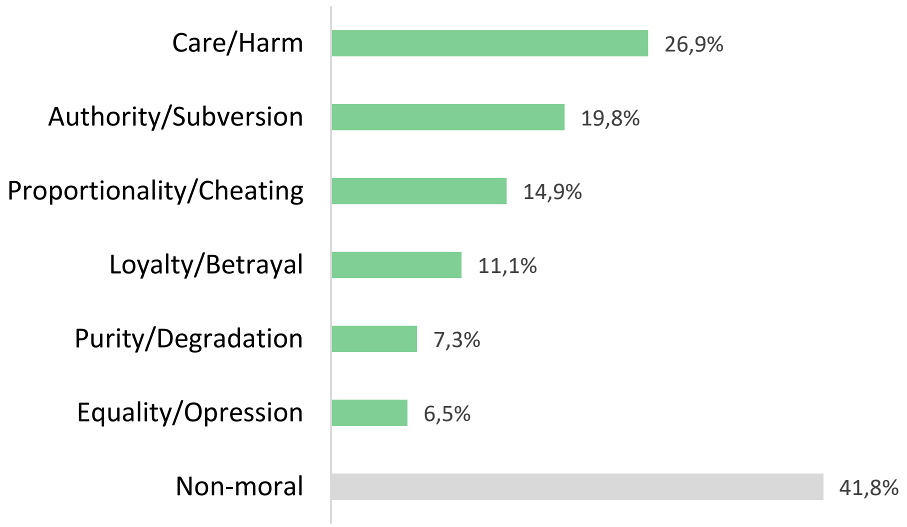

Figure 10 – Moral foundations by percentages of Daily Mail user comments (2012, N = 2021).

According to our assignment, 41,8% of all comments do not contain any explicit moral framing. This means that 58,2% of the 150,000 sampled comments could be categorized as invoking at least one moral foundation. This is a substantial proportion, suggesting that moral considerations play a significant role in the way users engage with news articles. While user comments serve multiple purposes—such as reacting to news events, expressing emotions, or engaging in political discourse—this data indicates that a large share of user contributions are explicitly framed in moral terms. Users frequently use moral language either to evaluate the ethical implications of news events or to signal moral concerns regarding the actions, policies, or societal developments they discuss. This underscores the moral dimension of public discourse, where users are not only reacting emotionally but also actively interpreting events through moral principles.

Among the moral frames, **Care/Harm** emerges as the most frequently referenced moral frame, appearing in over a quarter of all comments. This frame centers around concerns for human well-being, suffering, and harm prevention. Many user comments reflect a moral reaction to events perceived as harmful, focusing on the suffering of individuals or groups affected by events, political decisions, or social issues. Additionally, the discussion often includes normative judgments about the responsibility of protecting others from harm, which brings this moral frame close to the one of authority.

Authority/Subversion is indeed the second most frequently occurring moral foundation, which appears in nearly 20% of comments. This moral frame relates to discussions about legitimacy, respect for authority, and obedience to societal norms. Many comments in this category focus on leaders and institutions failing to meet expectations, making flawed decisions, or losing public trust. Conversely, some discussions also emphasize subversion, or the rejection of authority, raising concerns about individuals, political groups, or movements that challenge traditional hierarchies or refuse to comply with established social norms. The prevalence of Authority/Subversion suggests that a significant portion of user discourse revolves around the perceived stability—or instability—of leadership, governance, and institutional trust.

Ranked third is the **Proportionality/Cheating** foundation, referenced in approximately 17% of comments. This moral frame is rooted in the principle of fairness, but in a way that is typically associated with a rather conservative perspective on justice. It is based on the idea that rewards should be proportionate to effort and contributions, and that those who contribute more should receive greater benefits. Many discussions in this category reflect concerns over perceived unfairness, exploitation, or violations of merit-based principles. The presence of this moral frame suggests that questions of justice, fairness, and economic reward distribution are frequently debated in user comments.

At the lower end of the distribution, the **Equality/Oppression** foundation appears in only 6.5% of comments, making it the least frequently referenced moral frame. This moral foundation represents a more left-leaning or liberal conception of fairness, emphasizing the protection of marginalized groups, social justice, and resistance against oppressive systems. The relatively low prevalence of this frame, compared to Proportionality/Cheating, suggests that discussions in the Daily Mail comment section tend to focus more on individual merit and proportional fairness rather than systemic inequality and social justice issues.

The **Loyalty/Betrayal** foundation ranks fourth, appearing in just over 11% of comments. This moral frame concerns allegiance to social groups, political entities, or national identities, and the perceived fulfillment—or violation—of obligations associated with those affiliations. Discussions framed in terms of Loyalty/Betrayal often involve criticism of individuals or political figures who are seen as failing to uphold their commitments, as well as expressions of solidarity with certain groups or causes.

Finally, the **Purity/Degradation** foundation appears in just over 7% of comments. This moral frame is associated with concerns about physical and moral purity, contamination, or the preservation of traditions and cultural integrity. Discussions invoking Purity/Degradation often focus on perceived threats to societal values, the erosion of traditions, or issues related to bodily integrity and cleanliness. This frame is frequently found in discussions on topics such as public health, morality, and social change, where commenters express concerns about moral decay, corruption, or defilement.

The distribution of moral foundations in Daily Mail user comments reveals several key insights into how moral reasoning influences online discussions. The strong presence of moral framing in a majority of comments suggests that users are not merely expressing opinions but are actively interpreting news events through ethical and moral lenses. While Care/Harm is the dominant moral concern—consistent with widespread sensitivity to human suffering and harm—other foundations, such as Authority/Subversion and Proportionality/Cheating, also play a significant role in shaping public reactions. The prevalence of Authority/Subversion as the second most common moral frame highlights the centrality of trust and legitimacy in political discourse, particularly regarding governance, institutions, and leadership failures. The contrast between the higher frequency of Proportionality/Cheating compared to Equality/Oppression suggests that discussions within this dataset tend to reflect merit-based fairness principles rather than concerns about systemic inequality. Overall, the findings indicate that moral considerations are deeply embedded in the way users engage with news content. They highlight how moral values influence public discourse, political polarization, and user reactions to socio-political events.

Figure 11 illustrates the relationship between moral frames and specific sentiments, as identified using the NRC Dictionary Approach. Like the previous tables, this figure consists of three separate tables, each offering a different perspective on the connection between moral foundations and emotional expression. The first table presents the absolute number of sentiment-related words found in comments associated with each moral foundation. It is important to note that multiple classifications are possible—a single comment can belong to more than one moral frame, and it can also contain multiple sentiments. This dataset is based on the sample of 150,000 Daily Mail user comments. The second table normalizes these values by calculating the average number of sentiment-related words per comment within each moral frame. This is done by dividing the total number of sentiment-related words by the number of comments associated with a given moral frame. For example, comments classified under Care/Harm total 40,391 and, on average, contain 1.02 words expressing anger. This allows for a relative comparison of how frequently different sentiments are expressed within each moral frame. The third table highlights whether a sentiment is overrepresented or underrepresented within a particular moral frame compared to the overall average across all comments. This is calculated by subtracting the overall mean occurrence of a sentiment from its occurrence within a specific moral frame. Green bars indicate above-average sentiment expression, while red bars indicate below-average occurrence. For instance, in comments associated with Care/Harm, anger-related words appear 1.02 times per comment, whereas the overall average across all comments is 0.74 words per comment, resulting in a difference of +0.28. This means that anger is significantly overrepresented in comments framed by the Care/Harm moral foundation.

These three tables together provide a structured way to analyze which sentiments are most frequently associated with different moral frames, offering insights into how moral reasoning and emotional expression interact in user-generated discourse.

Category	Positive	Negative	Anger	Fear	Disgust	Sadness	Anticip.	Trust	Joy	Surprise	Comments
Care	88.975	88.406	41.351	52.425	30.734	46.214	46.939	56.977	37.797	23.117	40.391
Proportionality	47.364	38.381	18.407	20.397	12.388	18.619	23.991	30.561	18.841	11.700	22.368
Equality	23.674	21.232	10.609	11.941	7.410	10.452	11.189	15.240	9.117	5.303	9.748
Authority	70.404	67.151	31.169	40.029	21.199	30.780	34.346	48.350	24.713	17.476	29.743
Loyalty	38.168	30.507	14.805	16.308	10.143	15.338	18.991	25.140	16.371	10.000	16.638
Purity	22.145	22.922	10.614	12.258	9.285	10.983	11.223	14.130	9.292	5.583	10.974
Non_Moral	95.847	78.239	32.227	40.622	23.504	36.658	51.097	60.508	37.541	25.808	62.666
Total	**282.116**	**249.311**	**111.595**	**138.162**	**80.412**	**120.611**	**146.206**	**182.846**	**112.022**	**73.480**	**150.000**

Words per comment

Category	Positive	Negative	Anger	Fear	Disgust	Sadness	Anticip.	Trust	Joy	Surprise	Comments
Care	2,20	2,19	1,02	1,30	0,76	1,14	1,16	1,41	0,94	0,57	40.391
Proportionality	2,12	1,72	0,82	0,91	0,55	0,83	1,07	1,37	0,84	0,52	22.368
Equality	2,43	2,18	1,09	1,22	0,76	1,07	1,15	1,56	0,94	0,54	9.748
Authority	2,37	2,26	1,05	1,35	0,71	1,03	1,15	1,63	0,83	0,59	29.743
Loyalty	2,29	1,83	0,89	0,98	0,61	0,92	1,14	1,51	0,98	0,60	16.638
Purity	2,02	2,09	0,97	1,12	0,85	1,00	1,02	1,29	0,85	0,51	10.974
Non_Moral	1,53	1,25	0,51	0,65	0,38	0,58	0,82	0,97	0,60	0,41	62.666
Total	**1,88**	**1,66**	**0,74**	**0,92**	**0,54**	**0,80**	**0,97**	**1,22**	**0,75**	**0,49**	**150.000**

Difference to total

Category	Positive	Negative	Anger	Fear	Disgust	Sadness	Anticip.	Trust	Joy	Surprise	Comments
Care	0,32	0,53	0,28	0,38	0,22	0,34	0,19	0,19	0,19	0,08	40.391
Proportionality	0,24	0,05	0,08	-0,01	0,02	0,03	0,10	0,15	0,10	0,03	22.368
Equality	0,55	0,52	0,34	0,30	0,22	0,27	0,17	0,34	0,19	0,05	9.748
Authority	0,49	0,60	0,30	0,42	0,18	0,23	0,18	0,41	0,08	0,10	29.743
Loyalty	0,41	0,17	0,15	0,06	0,07	0,12	0,17	0,29	0,24	0,11	16.638
Purity	0,14	0,43	0,22	0,20	0,31	0,20	0,05	0,07	0,10	0,02	10.974
Non_Moral	-0,35	-0,41	-0,23	-0,27	-0,16	-0,22	-0,16	-0,25	-0,15	-0,08	62.666
Total	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**0,00**	**150.000**

Figure 11 – Distribution of sentiments across moral foundations (NRC sentiment approach, N = 150,000 Daily Mail comments, 2021).

Turning to the third table of Figure 11, which indicates whether a sentiment is over- or underrepresented within a given moral frame, we can identify clear patterns in the relationship between moral reasoning and emotional expression. **A key observation is that comments not assigned to any moral frame (labeled as non-moral in the table) consistently exhibit a below-average occurrence of sentiment-related words, as indicated by the red bars**. This suggests that comments without explicit moral framing tend to contain fewer emotionally charged words. Conversely, in nearly all cases, comments that are associated with a moral frame show above-average sentiment expression, as reflected by the green bars. This finding is significant, as it strongly suggests that comments framed in moral terms express a higher degree of emotional intensity than those lacking a moral perspective. In other words, moral framing is closely linked to emotional expression, reinforcing the idea that when users discuss moral values or moral violations, they tend to do so in an emotionally charged manner.

While emotional expression is, of course, also present in other types of narrative framing, this data indicates that moralized discourse is particularly emotion-laden. The connection between moral values and emotions is therefore not incidental but rather a core feature of moral reasoning in user-generated discourse. This finding underscores the powerful role of moral concerns in shaping public discussions, as moral frames appear to heighten emotional engagement in ways that other narrative structures may not. Let's now examine the relationship between specific moral frames and sentiments.

Among the moral frames, Equality, Authority, and Loyalty are most frequently associated with **positive emotions**. This suggests that when equality is upheld, authorities act effectively and earn public trust, or loyalty is reinforced, users tend to react with positive sentiments. Specifically, the Loyalty frame is frequently accompanied by positive sentiment, as users express satisfaction when commitments, social obligations, and allegiances are honored.

However, Authority plays a dual role. While it is associated with positive emotions when institutions function effectively, it is also a key driver of **negative emotions** when authority is perceived as failing or abusive. Similarly, Care/Harm generates negative emotions when harm is perceived, particularly when news events highlight suffering, injustice, or preventable crises. Equality, though linked to positive sentiment when fairness is upheld, also evokes negative emotions when users perceive violations of fairness and justice.

Anger is one of the most politically significant emotions because it has a strong mobilizing effect (Erisen, 2020). The data shows that anger arises particularly in response to violations of Equality and Authority, as well as instances of harm. This suggests that public discourse becomes especially heated when issues of fairness, governance, and harm prevention are at stake. Anger often reflects frustration with injustice, dissatisfaction with leadership, or indignation over harm inflicted on others. Given the role of anger in political mobilization, it is no surprise that political and social movements frequently center around narratives that emphasize violations of equality, the abuse of authority, or preventable harm.

Fear is another significant negative emotion, in our data particularly associated with Authority and Care/Harm. Fear arises when authorities are perceived as failing, acting abusively, or losing legitimacy. Additionally, fear is closely linked to harm-related concerns, as users express anxiety over threats to well-being, public safety, or insufficient protective measures.

Disgust is particularly associated with the Purity/Degradation frame. This follows established concepts, which suggest that purity violations—whether concerning physical integrity, social norms, or moral decay—trigger strong disgust reactions (Horberg et al., 2009). Discussions surrounding bodily autonomy, contamination, or perceived moral corruption often evoke disgust-driven rhetoric. A clear example of this can be found in debates over child abuse, where disgust reactions are particularly intense. Another example is the discussion of mandatory vaccinations, which vaccine skeptics have framed as an infringement on bodily integrity, leading to expressions of disgust.

Sadness appears most frequently in discussions related to Care/Harm, particularly when news events highlight suffering, victimization, or loss. This confirms the deep emotional connection between moral concern for others and expressions of grief or distress. Given that moral discourse often focuses on harm and protection, it is logical that sadness would be a prevalent response to events involving human suffering, injustice, and crisis situations.

Among positive emotions, **anticipation** is strongly associated with Care/Harm. This suggests that users express optimism when harm is prevented, minimized, or addressed. Similarly, anticipation is linked to Authority, implying that people expect authorities to take action and implement protective measures. **Trust** appears frequently in discussions related to Authority, but in a positive sense. This indicates that when institutions function effectively, or when leadership is seen as competent, trust in governance is reinforced. The presence of trust also suggests that not all discourse on authority is negative—some users express confidence in leadership and institutions when they believe these entities fulfill their responsibilities. **Joy**, while generally less prevalent than negative sentiments, is most frequently associated with Loyalty. This suggests that users experience satisfaction and happiness when loyalty, duty, and social cohesion are upheld. Meanwhile, **Surprise**, though infrequent, also appears in connection with Loyalty, possibly indicating that users react unexpectedly to events involving shifting allegiances, betrayals, or unexpected demonstrations of commitment.

The findings reveal **clear connections between moral frames and specific emotions**. Among negative emotions, anger is mobilized by violations of equality and harm, fear arises when harm is anticipated and authority is questioned, and disgust is primarily triggered by purity-related concerns. Positive emotions are less frequent but emerge when moral expectations are fulfilled—trust is linked to effective authority, joy to loyalty, and anticipation to harm prevention.

Given that moral framing is inherently linked to emotional intensity, it is no surprise that news comment sections and discussion forums thrive on moralized discourse. These platforms facilitate user interaction and engagement and are built upon the emotional sharing of moral concerns. The success of these platforms is partly due to their ability to amplify emotional responses to moral violations, making them ideal spaces for discourse that is highly charged, polarized, and socially influential. Understanding the emotional underpinnings of moralized discourse allows us to better interpret political and social dynamics online, particularly in spaces where emotions drive engagement, influence public opinion, and shape digital activism. This analysis underscores that moral reasoning is not just a cognitive process—it is deeply emotional, shaping how people interpret, react to, and engage with societal issues.

5. Key Insights

Overall Sentiment of Daily Mail User Comments

- The sentiment analysis of 150,000 Daily Mail user comments reveals a slightly **negative overall sentiment**, with **52% of comments** exhibiting a negative sentiment and **48% a positive one**.
- Negative emotions, particularly **fear, anger, and sadness**, dominate user discussions, often driven by topics perceived as controversial or emotionally charged.
- While positive sentiment words appear frequently, their impact is often diminished due to the **context in which they are used**.

Sentiments of Different Categories of Articles

- **Health, News, and Debate** articles generate the most **negative sentiment**, particularly **fear and anger**. Health-related discussions, especially those on **COVID-19**, evoke strong fear responses.
- **Sports, Money, and Lifestyle (Femail)** articles tend to elicit **positive sentiment**, with emotions like **joy and trust** being more common.
- **Entertainment and Travel** articles generally provoke **positive engagement**, while categories such as **Property and Science & Tech** show a more **neutral balance** of sentiment.

Correlation Between Specific Topics and Sentiments

- **COVID-19 and Vaccination** dominate user discussions, accounting for **over 38% of topic-related comments**. These discussions are largely **negative**, with **fear and distrust** being the primary emotional responses.
- **Crime and Law Enforcement** elicit **anger and fear**, making them one of the most emotionally charged topics.
- **Media Bias and Journalism** discussions display strong **negative sentiment**, often expressing **distrust in "mainstream" media**.
- **Royal Family and Sports** discussions are exceptions, generating **positive sentiment**, with **joy and admiration** being dominant emotions.
- The study indicates that **highly discussed topics tend to be more polarizing**, with both strong negative and positive sentiments appearing frequently.

Prevalence of Moral Foundations in User Comments

- **58.2% of comments** contain **explicit moral framing**, showing that **moral considerations play a significant role** in shaping user discussions.

- The most referenced moral foundation is **Care/Harm**, found in **over 25% of comments**, often focusing on suffering, victimization, and protection.
- **Authority/Subversion (20%)** and **Proportionality/Cheating (17%)** are also prominent, frequently linked to discussions about governance, fairness, and institutional trust.
- **Loyalty/Betrayal (11%)** and **Purity/Degradation (7%)** appear less frequently but are strongly associated with discussions on **social cohesion, tradition, and morality**.
- **Equality/Oppression (6.5%)** is the least mentioned moral frame, indicating that discussions in this dataset focus more on **merit-based fairness than systemic inequality**.
- Moralized discourse tends to be **more emotionally charged**, reinforcing **polarization and engagement** with divisive narratives.

Correlation Between Specific Moral Foundations and Sentiments

Moral framing is closely linked to **emotional intensity**, with different moral foundations **evoking distinct emotional responses**:

- **Care/Harm → Fear and Sadness**: Users react with **fear** when harm is perceived as imminent (e.g., public health risks, crime) and with **sadness** when discussing suffering or loss.
- **Authority/Subversion → Fear and Anger**: Negative emotions arise when authority is seen as failing, abusive, or illegitimate. **Fear** emerges in discussions of governance failures, while **anger** appears when institutions are perceived as corrupt or oppressive.
- **Proportionality/Cheating → Anger and Distrust**: Users express **anger** toward perceived unfairness in economic policies, wealth distribution, or corruption scandals. **Distrust** is common in discussions about political and financial elites.
- **Loyalty/Betrayal → Anger and Disappointment**: Users react negatively when political figures, national institutions, or public figures are seen as betraying their responsibilities.
- **Purity/Degradation → Disgust and Moral Outrage**: Discussions involving issues like **vaccinations, immigration, and social change** frequently evoke **disgust**, reflecting concerns about moral decay, contamination, or corruption.
- **Equality/Oppression → Anger and Moral Indignation**: When equality is perceived as violated, users express **anger**, particularly regarding social justice issues or perceived systemic injustices.

Our study has demonstrated a clear link between specific topics, disinformation, and conspiracy theories on the one hand, and moral framing, moral foundations, the violation of moral values, and distinct emotional responses on the other. This finding underscores the importance of not only fact-checking, media literacy, and public education—critical as they are—

but also understanding why such content appeals to many individuals. Our analysis shows that this content is compelling because it is morally framed, addressing values that people deeply hold and consider fundamental to their worldview. User comments reflect these moral concerns, revealing how individuals interpret information through the lens of their moral beliefs, which in turn shape their opinions, attitudes, behaviors, and social relationships. We think, our study employs an innovative methodological approach, as it systematically examines the relationship between moral framing and emotions—an analysis that, to our knowledge, has rarely or not yet been conducted in this way using Large Language Models (LLMs). This approach allows for a nuanced understanding of how moral and emotional dimensions interact in digital discourse, contributing to the growing body of research on the persuasive nature of morally framed content. We found that discussions of moral values and perceived moral violations are consistently accompanied by intense emotional reactions, reinforcing the connection between moral reasoning and emotional engagement. This suggests that countermeasures which only act at a rational level are insufficient on their own. To effectively mitigate the impact of disinformation and polarizing narratives, interventions must also consider the moral and emotional dimensions that make such content so persuasive. This perspective moves beyond the individual level, extending into broader societal dynamics, highlighting the need for a more comprehensive approach that acknowledges the interplay between content, moral values, and emotions in shaping digital discourse and public opinion.

6. Conclusion and Recommendations

The following recommendations are derived from the findings of our research on the role of emotionalization and moral framing in the spread of misinformation, disinformation, and harmful content in digital spaces. Recognizing that polarization is both a systemic and psychological phenomenon, the proposed measures address three levels of intervention: (1) political measures beyond social media regulation, (2) regulation of digital platforms, and (3) individual-level strategies for users and public discourse. While of course some of these recommendations are a challenge to implement (in general or due to current political circumstances and economic constraints), it remains critical to acknowledge their necessity in fostering a healthier digital information ecosystem and mitigating the detrimental effects of online polarization. It is also clear that many of these measures are not new, have already been considered or initiated, but their implementation appears increasingly difficult – and important! – in light of the current situation.

6.1. Political Measures Beyond Social Media Regulation

- **Address Socio-economic and Structural Causes of Polarization**: Political and societal polarization is not solely a product of social media but also a reaction to broader socio-economic transformations. Policymakers should address these underlying drivers, although it is clear that such interventions are difficult to implement in the current political climate. Nevertheless, acknowledging their necessity remains crucial.

  - ***Recognizing the economic vulnerability of the middle-aged age group****, political measures must address their growing insecurity amid rapid societal changes. Automation and digitalization disproportionately impact older workers, who face skill mismatches and limited retraining options. Meanwhile, precarious employment and declining job stability heighten their risk of redundancy, unemployment, and financial hardship. Shrinking pensions and stagnant wages leave many caught between instability and retirement without adequate savings or protections. This economic distress fosters societal discontent, making individuals more susceptible to disinformation and polarization. To counteract these risks, governments must implement comprehensive retraining programs, job transition support, and policies promoting stable employment. Lifelong learning and accessible reskilling initiatives are crucial to ensuring older workers remain active in an increasingly digital economy, mitigating the anxieties that drive political and social instability.*

- **Combat Social Inequality**: The increasing gap between wealth groups fosters resentment and fuels polarization. Social and economic policies should aim to mitigate wealth disparities, even though large-scale redistribution is politically challenging.

  - *Targeted measures should further address the* ***economic marginalization of middle-aged people****, who face job insecurity due to age discrimination, limited retraining, and rigid employment structures. Shrinking pensions and weakened safety nets leave many financially vulnerable, especially amid job displacement and precarious work. Rising living costs and intergenerational pressures further strain their stability, fueling frustration and susceptibility to disinformation. To counter this, policymakers should secure stable employment, strengthen pensions, and reduce financial barriers. Expanding retraining programs, enforcing anti-age discrimination laws, and adopting social protections are crucial to preventing further exclusion and mitigating political and social polarization.*

- **Invest in Social and Material Infrastructure**: Many societies in Europe face outdated or insufficient social infrastructures, contributing to economic insecurity and social tensions. While comprehensive reform may not be immediately feasible, recognizing the impact of these deficiencies is essential.

  - *In some European countries, e.g., Germany, prolonged austerity policy has stalled investment in critical infrastructure—transportation, public services, healthcare, and education—contributing to public distrust in government. Insufficient maintenance of roads, railways, and essential facilities fuels perceptions of state inefficiency, particularly in rural and economically weaker regions.* ***Middle-aged and older individuals****, who rely heavily on public infrastructure, face reduced access to services, deepening frustration and distrust. This discontent has been linked to rising support for right-wing populism, which exploits* *narratives of governmental failure. To counter this, policymakers must prioritize infrastructure investment to restore public confidence and ensure state institutions remain functional and responsive.*

- **Manage Transformational Shocks:** This is important, as the effects of digitalization, climate change, and geopolitical conflicts exacerbate uncertainty. Policies should aim to mitigate both material and symbolic disruptions caused by these changes, addressing economic decline, job losses, and social mobility constraints while also acknowledging perceived threats to cultural identity and established social norms.
    - ***Middle-aged individuals*** *are specifically affected by economic and technological disruptions, as they face job losses from deindustrialization, increased competition from China, and automation-driven labor market shifts. Digitalization favors younger workers, while climate policies accelerate structural changes in carbon-intensive industries, forcing premature career transitions. These uncertainties heighten economic anxiety, making this demographic more susceptible to populist and disinformation narratives that exploit fears of decline. Policymakers must implement targeted career transition programs, financial protections, and retraining initiatives to support adaptation and prevent further social and political polarization.*
- **Acknowledge Emotional and Moral Dimensions**: Policies should recognize that emotional reactions to socio-economic transformations are often rooted in perceived moral violations and identity threats. Addressing these grievances in a way that resonates across ideological divides is a significant challenge, but possible by reframing them as moral injuries rather than as social struggles over interests or the legitimacy of emotions. This approach shifts the focus from confrontation to recognition, making it easier to foster mutual understanding and constructive dialogue.
    - ***Middle-aged individuals*** *are particularly sensitive to socio-economic transformations that challenge long-held values, social roles, and identities. Job losses due to deindustrialization, digitalization, and global competition are often perceived not just as economic setbacks but as moral injustices—violations of fairness, loyalty, and societal stability. Many in this age group feel increasingly disconnected from political and cultural shifts, interpreting rapid societal change as a loss of status and recognition. This perceived erosion of their social and economic standing fosters resentment and makes them more receptive to populist narratives and disinformation that frame these disruptions as deliberate betrayals. Policies addressing disinformation must acknowledge these moral grievances, reframing them as legitimate concerns rather than ideological conflicts.*

6.2. Regulation of Social Media Platforms

- **Restructure the Business Model of Emotional Amplification:** The core business model of social media platforms is based on amplifying emotional and polarizing content. Regulations should aim to curb algorithmic prioritization of divisive content, similar to initiatives like the EU Digital Services Act (DSA).
- **Reform Platform Liability**: The U.S. Communications Decency Act (CDA), particularly Section 230, grants platforms immunity from content liability. Policy efforts should push for revisions that hold platforms accountable for content amplification while preserving free speech, though legislative change in this area remains politically contentious.
- **Strengthen Content Moderation and Management**: Platforms should implement and enforce stricter content governance policies, including:
  - *Content Removal & Demotion*: AI-driven moderation combined with human oversight.
  - *Fact-Checking & Labeling*: Platforms should provide clearer context for misleading content.
  - *Downranking Harmful Content*: Algorithmic demotion of disinformation, conspiracy theories, and extremist content.
  - *Transparency in Algorithmic Decisions*: Platforms must disclose how they promote or suppress content.
- **Legal Penalties for Harmful Content**: Strengthen regulatory frameworks to penalize platforms that fail to curb misinformation and hate speech effectively, though enforcement remains a challenge.
- **Ensure Effective Enforcement of EU Regulations**: Current initiatives such as the EU Code of Practice on Disinformation must transition from voluntary commitments to legally binding obligations. However, enforcement mechanisms remain inconsistent and politically contested.
- **Broad Societal Impact of Platform Regulation**: The regulation of social media platforms is not specific to any single age group but is crucial for safeguarding democratic discourse and public trust across all demographics. Middle-aged individuals, like other users, would benefit from measures that curb disinformation, reduce algorithmic amplification of harmful content, and enhance transparency. However, the enforcement of such regulations faces increasing geopolitical challenges. With Donald Trump's return to the U.S. presidency after the 2024 election, the United States is no longer a reliable partner for the European Union in addressing platform governance. Instead, a strategic alignment between the U.S. and Russia raises concerns about efforts to undermine European democracies, making it significantly harder for the EU to regulate global platforms based in the U.S. and China. Despite these obstacles, establishing effective regulatory mechanisms remains essential for countering digital threats to democratic stability.

6.3. Individual-Level Measures for Users and Public Discourse

- **Foster Respectful Engagement with Emotions**: Addressing misinformation and polarization requires an approach that does not alienate individuals through condescension or overtly pedagogical methods. People are more likely to reject information if they feel patronized or dismissed. Public figures, policymakers, and media professionals should therefore be mindful of their rhetoric, as dismissive language exacerbates social divides rather than bridging them. (A notable example is Hillary Clinton's "basket of deplorables" remark from September 2016, which fueled resentment and deepened political antagonism[2]). Instead of categorizing groups in a reductive or derogatory manner, discourse should acknowledge emotions and concerns, fostering an environment where difficult conversations can take place constructively ("safe space for unsafe conversations").
- **Acknowledge the Reciprocal Nature of Polarization**: Political and ideological polarization does not occur in isolation, nor is it solely the fault of one side. Rather, it is a reciprocal dynamic in which opposing ideological groups reinforce one another's narratives, often reacting to perceived attacks or injustices. Recognizing this mutual reinforcement is essential for developing strategies that de-escalate conflicts rather than intensify them. Rather than framing polarization as a struggle between a morally superior and an inferior group, interventions should highlight the structural and psychological mechanisms that drive polarization. A more nuanced understanding of this phenomenon can help foster constructive engagement across ideological divides.
- **Recognize Emotional Reactions as Responses to Moral and Identity Threats**: Emotions expressed in digital discourse are often rooted in deeper moral and identity-based concerns rather than mere disagreements over facts. Many individuals react strongly online because they perceive certain events, narratives, or policies as a direct challenge to their social identity, cultural values, or sense of justice. Addressing polarization, therefore, requires an approach that acknowledges these underlying concerns rather than dismissing them outright. Recognizing that different groups experience distinct forms of moral injury—even when their worldviews conflict—can create opportunities for de-escalation and mutual understanding.
- **Move Beyond Fact-Checking Alone**: Traditional fact-checking efforts, while important, often fail to change perspectives and can even reinforce pre-existing beliefs due to psychological reactance. When individuals feel that their worldview is being challenged in a didactic manner, they tend to double down on their beliefs rather than reconsider them. Alternative approaches should therefore complement fact-checking by addressing misinformation at a more fundamental level:
    - *Prebunking and Psychological Inoculation*: Instead of merely countering misinformation after it spreads, users should be educated on how misinformation works

[2] https://en.wikipedia.org/wiki/Basket_of_deplorables, last access 2025/02/12.

before they encounter it. This approach, inspired by inoculation theory, makes people more resistant to manipulation tactics.

  - *Media Literacy Programs*: Critical engagement with digital content should be encouraged from an early age. Educational institutions should integrate media literacy training that helps individuals assess sources, detect bias, and recognize disinformation tactics.
  - *Counter-Speech and Alternative Narratives*: Rather than relying solely on institutional actors to counter misinformation, trusted community figures—such as athletes, religious leaders, educators, and local influencers—should be engaged in spreading corrective or alternative narratives in ways that resonate with their communities.

- **Encourage Realistic Engagement with Societal Transformations:** Many individuals turn to social media as an emotional refuge from overwhelming societal transformations, such as digitalization, economic decline, cultural shifts, and climate change. In some cases, the expression of anger, resentment, or conspiracy thinking serves as an outlet for frustration over changes that feel beyond one's control. Policies and interventions should enable individuals to process these changes more constructively, offering alternative frameworks for understanding transformation rather than leaving them vulnerable to reactionary narratives. This may involve public education campaigns, economic support programs, and social initiatives that help people adapt to inevitable changes rather than resisting them in counterproductive ways. This would mean shifting the discussion away from the concept of truth toward that of reality, in the sense that right-wing political movements are waging more of a war against reality than a war against truth—with the hope that we might find it easier to reach a common understanding of reality rather than truth.
- **Mitigate the Negative Effects of Digitalization on Public Discourse**: Digitalization has reshaped public discourse by amplifying emotional reactions, reducing the space for reflective engagement, and accelerating the spread of extreme content. The insecurities caused by rapid technological transformation contribute to reactionary emotional responses, particularly when traditional sources of stability—such as jobs, communities, and cultural norms—are perceived as being eroded. Policymakers, educators, and media professionals should develop strategies to slow down the pace of online discourse, allowing for more thoughtful engagement rather than reactive emotional outbursts. Additionally, users should be encouraged to develop digital resilience, which includes recognizing manipulative online tactics, fostering emotional regulation in digital spaces, and engaging in self-reflective consumption of content.

- **Explicitly Address Moral Violations in Counter-Measures**: Much of the emotional intensity observed in online discourse stems from perceived moral grievances, which fuel outrage, defensiveness, and polarization. Simply countering misinformation with factual corrections does not address the deeper sense of injustice that often underlies these emotional responses. Instead of dismissing these grievances or focusing only on factual inaccuracies, counter-measures should explicitly acknowledge moral injuries in a way that fosters respect and dialogue rather than hostility. This means recognizing that while negative emotions (anger, resentment, fear) should not necessarily be validated, the underlying concerns that generate them must be addressed. For example, when individuals react strongly to discussions about social change, they may not only be rejecting the facts but also expressing deeper anxieties about loss, displacement, or betrayal. Responses should be framed in ways that indicate an understanding of these concerns, making it clear that while not all reactions are justified, the sense of injustice that fuels them is acknowledged. Doing so can help reduce defensiveness and open pathways for more constructive conversations.

6.4. Moral Foundations and Age: Value Shifts in Middle-Aged Populations

Research on Moral Foundations Theory (MFT) demonstrates that moral values shift with age, influencing how different age groups engage with political narratives, misinformation, and social discourse. **Younger individuals** tend to prioritize individualizing foundations (Graham et al., 2009), such as **Care and Fairness**, which emphasize personal rights, harm avoidance, and equality. In contrast, **middle-aged and older adults** are more likely to endorse binding foundations (ibid.), including **Loyalty, Authority, and Purity**, which focus on group cohesion, respect for hierarchies, and maintaining traditional social structures. This shift in moral emphasis has significant implications for understanding the emotional and psychological appeal of certain political and ideological narratives among older populations (Sağel, 2015; Castilla-Estévez, 2021; Friesen, 2019).

As individuals age, their increasing reliance on binding moral foundations makes them more receptive to messages that emphasize stability, duty, and in-group solidarity. Political actors, disinformation campaigns, and extremist movements often exploit these values by framing societal change as a threat to tradition, portraying institutions as either protectors of order or agents of its decline. Misinformation and conspiracy theories that invoke perceived violations of authority, loyalty, or purity—such as narratives about government betrayal, cultural degradation, or moral corruption—are particularly effective in mobilizing middle-aged and older audiences. Understanding these moral sensitivities is essential when designing interventions to counteract disinformation and polarization.

Public discourse and policy initiatives should account for these moral predispositions to develop more effective strategies for engaging middle-aged individuals in constructive ways. Also here, rather than solely relying on fact-checking or rational debunking – methods that often appeal to younger audiences' fairness-based reasoning – counter-narratives should also address the moral and emotional dimensions that shape older individuals' worldviews. For example, framing democratic institutions as guardians of societal stability, rather than as agents of disruptive change, may enhance their credibility among this demographic. Similarly, reinforcing narratives of social cohesion and collective responsibility, rather than emphasizing abstract ideals of equality, can foster greater receptivity to counter-disinformation efforts.

Recognizing the moral landscape of different age groups is crucial for mitigating the impact of digital misinformation and fostering more inclusive public discourse. By acknowledging the distinct moral concerns of middle-aged individuals and integrating these insights into policy and communication strategies, it becomes possible to counteract the appeal of polarizing and manipulative content more effectively.

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