Decoding Spoken Reactions to Political News in the Digital Age: An Audio-Based Machine Learning Study of Emotions

Candidate Number: 22894

London School of Economics and Political Science

Supervisor: Dr. Daniel de Kadt

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Abstract

This paper borrows theory and methods from the field of computational linguistics to analyse whether different types of political media can influence a reader's emotional state. It investigates whether exposure to political news articles in the style of born-digital media is associated with an increased prevalence of negative emotions and whether those negative emotions can be classified as high-arousal in nature. It also investigates demographic trends seen in the expression of emotions following exposure to experimental stimuli. The paper employs a unique survey methodology to gather audio clips from 52 participants and leverages a hidden Markov modelling technique to compare the audio features of these clips to audio where the speaker's emotional state is known. The use of audio data allows this paper to move beyond traditional (and often biased) methods of emotion recognition, such as textual cues or participant self-reporting.

Contents

1 Introduction

High levels of exposure to political news have motivated past scholars to investigate the unique influence that media holds in political society. Research has shown the power of media to shape opinions, motivate changes in political behaviour, and even drive institutional agendas (Firmstone, 2019) (McCombs and Shaw, 1972). Recently, political media has also been shown to have substantially increased in diversity of thought, journalistic style, and dissemination technique. The commercialization of information and communication technologies in particular has led to the increasing popularity of online news and the birth of new, all-online media companies, called born-digital outlets (Višňovský et al., 2017). We can posit from a synthesis of past literature that these outlets have been important figures in the rise of sensationalist politics globally, through their frequent publication of exciting but divisive content that is linked to their distinct business models (Wilding et al., 2018). As this paper will show, born-digital outlets often produce content with emotionally charged language and greater levels of subjectivity. This finding, combined with the increasing salience of born-digital outlets (Vara-Miguel, 2019), motivates an understanding of the emotional states that result from reading this type of political news. It especially highlights the importance of determining whether these outlets lead to negative emotions that are heavily linked to shifts in political behaviour. While numerous past studies have explored traditional media content and its impact on general political discourse, very few have devoted considerable time to the study of born-digital news or consumer-side emotional effects of political media exposure.

This capstone project will employ an experimental survey methodology and unique computational tools that allow us to uncover consumer responses linked to this particular subset of online news in the United Kingdom. It will take particular focus on differentiating participants' emotional responses to media in the style of born-digital and legacy media, but it will also provide a holistic overview of the way in which the population on a whole responds to negative media. Attention will also be devoted to highlighting demographic trends in the observed emotional responses. It will accomplish all of this through the use of machine learning techniques and audio data.

The paper will begin with an overview of previous literature on the role of media in politics, the evolving media landscape and the popularization of born-digital media, as well as how emotions play a role in shaping political opinions and decisions. This will be followed by specific research questions identified from gaps in the literature, as well as testable hypotheses formulated from the overview of past works and existing theory. There will then be a detailed overview of the unique methodology that this paper employs to explore the research questions, including an overview of the approach used to collect participant utterances (short clips of speech), the advantages of using audio data in the context of this research, as well as the computational methods for parsing, processing and analysing this audio. It will explain how these approaches build on the work of previous scholars and substantially add to the corpus of work on speech processing methodology.

We will then move on to the more substantive pieces of the paper, the first of which will involve the presentation of analytical results and how they relate to the research questions posed in an earlier chapter. There will be a brief overview of whether the analysis supports the paper's hypotheses before moving on to a discussion of the real-world implications of these findings, including what they could mean for the direction of British politics. In this chapter, results will also be linked back to the literature review to demonstrate how any findings add to topical knowledge of political media and communication. This paper will then provide an overview of the limitations of the methods used, as well as how the models' performance invites a further debate into their continued use. It will end by proposing several further topical and methodological avenues that future researchers might explore to build on this work.

2 Literature Review

This literature review aims to contextualize the wider research setting in this paper through a discussion of previous studies relating to the role of news media in politics, the transformed media landscape in the digital age with the birth of born-digital news platforms, and the role of emotions in politics. It will begin by introducing research that has examined news media's ability to impact public opinion, voting behaviour and institutional agenda setting. It will then engage with authors who have studied the emergence of fully digital media platforms and found a wide range of differences between born-digital and legacy media. Past research will also show why we might expect the journalistic content to differ between these two outlet types. The subsequent section will review published studies discussing the role of emotions in politics; it will show that politicians benefit from engineering their language to elicit emotions in the electorate and briefly mention their strategic use of media to accomplish this. It will also engage with authors who have studied psychological theories of arousal to show that specific emotions have the potential to spark behavioural action amongst voters. Lastly, it will include mentions of where previous literature has fallen short of fully exploring a concept or theory, motivating the analysis later in this paper.

2.1 Role of Media in Politics

The role of news media in politics has been widely studied by previous authors, who have discussed how it can impact public opinion, tangible behaviour, and political agendas. Countless studies have been devoted to establishing causal links between partisan news and a reader's political views; however, researchers have long questioned whether news shapes the beliefs of readers or whether a reader's pre-existing beliefs shape their choice of news consumption. Earle and Hodson engaged with this question through the use of a cross-lagged longitudinal model that controlled for pre-existing sociopolitical views. They found strong evidence to suggest that left-leaning news outlets pulled the political views of their readers further to the left of the political spectrum while right-leaning outlets pulled their readers' views to the right (Earle and Hodson, 2022). On the contrary, the authors reported finding less strong evidence that pre-existing beliefs significantly impact choice of outlet. This appears to be a topic of ongoing debate in the research community, with other studies publishing conflicting evidence (Stroud, 2008). Another paper has shown the ways in which editorial pieces can impact public opinion, particularly among those who are less politically informed (Firmstone, 2019). While this piece of research focuses specifically on blatant displays of partisanship by newspapers, other authors have extrapolated these findings and shown that more covert biases also shape the political opinions of readers (Druckman and Parkin, 2005).

Beyond shaping public opinion, political media has been shown to influence electoral participation. A 2023 paper engaged with psychological theories positing that repeated exposure to a stimulus can lead that stimulus to be viewed more favorably. Using an experimental design, the author found that a participant's frequent exposure to neutral stories about a fictitious candidate was associated with an increased likelihood that the participant would vote for that candidate in a mock election (Pfister et al., 2023). These findings led the author to caution media outlets against disproportionate coverage of candidates during a campaign cycle, highlighting the capacity for this imbalance to influence electoral outcomes. Another paper found a positive association between consumption of likeminded media and propensity to participate in campaign activity (i.e. donating to a political party, attending a political event or displaying a sign in support of a candidate) (Dilliplane, 2011). A paper by DellaVigna and Kaplan found additional evidence of behavioural changes resulting from exposure to right-wing media. The authors used a difference-in-differences estimator and found that in towns where Fox News was made available by 2000, the Republican Party increased their vote share in the presidential election. They additionally pointed to a similar increase seen in smaller races that weren't discussed in Fox News coverage, suggesting that the news outlet triggered an ideological shift among its viewers (DellaVigna and Kaplan, 2007).

Lastly, political news has been shown to influence the public agenda. Literature showing that media instructs the public to think about certain political issues led to the formation of McCombs and Shaw's agenda-setting theory. Their research argues that coverage given to certain issues by the mass media results in the topic entering the public agenda (McCombs and Shaw, 1972). Issues that are more salient in the mass media are consequently perceived as having greater importance by the public, leading politicians to respond accordingly by engaging with the issue in the government sphere. This theory remains important in the field of public policy and continues to influence emerging research. Through engaging with the diverse ways in which mass media can influence the opinions, behaviour, and institutional agenda within a political system, all of these authors have motivated research pursuing a deeper understanding of individuals' response to media exposure.

2.2 Evolving Media Landscape and Born-Digital News

The emergence of the internet and the popularization of online news has led to a rapid diversification of the media consumed by people every day (Vara-Miguel, 2019). This has enabled the establishment of news outlets operating in an exclusively digital space. Previous authors have studied this emergence of non-traditional media and coined a term for the new online platforms: 'born-digital' news outlets. In contrast to legacy outlets that have TV, radio or print publications, such as the BBC or the Guardian, born-digital outlets have only ever existed online (Nicholls et al., 2016). It is important to note the distinction between born-digital outlets and the online extensions of legacy brands who have supplemented their traditional content with a new digital presence.

Vara-Miguel found that online news is still dominated by the digital publications of legacy outlets; however, he emphasizes that born-digital platforms have become an increasingly integral part of the online media landscape in the European countries his research analysed (Vara-Miguel, 2019). Certain evidence suggests that the emergence of born-digital media in the UK may be slightly weaker than in other Western European countries, but these papers were published nearly a decade ago (Nicholls et al., 2016). Given the constantly evolving nature of mass media, reproducing the methods in these papers using more recent data could give a better snapshot of the born-digital landscape in the UK.

Born-digital outlets tend to have a different distribution strategy to legacy media brands due to their reliance on online engagement as opposed to TV viewership or print subscribers. These publications have often been based around one website, but due to the popularization of receiving news via social media, their operations must now extend to sites like X and Facebook (Shabbir et al., 2016). It is increasingly true that readers do not visit the URL of a news outlet, but are exposed to their content through external social media sites or search engines (Shabbir et al., 2016). This has led many born-digital outlets to favor the publication of more engaging but divisive content that is more 'shareable', or in other words, has the potential to generate more likes and shares on social media sites (Wilding et al., 2018). The ability to produce shareable news that performs well in search algorithms and on social media could make a difference in the survival of a media company without television viewers or newspaper subscribers (Berger and Milkman, 2012). Harcup and O'Neill's previous work argued that the 'shareability' of an article is heavily linked to emotions – specifically, shareable news tends to make readers feel either strong positive or negative emotions (Harcup and O'Neill, 2017). While this literature sets an expectation for the type of content that might be widely seen on born-digital news platforms (content garnering strong emotional responses), the lack of research aimed at understanding how born-digital content actually impacts the emotions of readers is surprising.

The above research provides a synthesis of born-digital media and demonstrates key differences between the outlet types that will be central to the analysis of this paper. It is important these papers are recognized alongside the research introduced in the first section of this literature review, which discussed the power of media to shape opinions, behaviour, and the public agenda. If born-digital outlets are becoming a greater force in the political media landscape and are heavily motivated to publish emotional and shareable content, the role of these outlets in political spheres must be given more attention by researchers. This paper aims to address this gap by looking at consumer-side effects of born-digital outlets and providing an in-depth discussion about their wider impact on political discourse and electoral politics. Similar papers, to knowledge, do not currently exist.

2.3 Role of Emotions in Politics

As discussed in the previous section, born-digital outlets are becoming increasingly important actors in the media landscape and likely have considerable sway over the political content that is being consumed by the public. The literature also suggests that these outlets are likely to produce emotional content. To fully understand the capacity of born-digital outlets to shape politics, it is important also to understand the complex relationship between emotions and politics, and how emotions are strategically engineered by politicians and other political actors.

Many authors have explored the relationship between emotions and political views. In his 2007 book, Drew Westen examines the way in which political candidates and elected officials carefully shape their language to prompt certain emotional responses from voters (Westen, 2007). Westen argues that politicians should frame their message emotionally to be successful, as the general public respond positively to emotional connections with candidates. He further argues that policies often only matter as far as they evoke an emotional response from a voter (Westen, 2007). Politicians often rely on the media as a vehicle for the delivery of this emotional content to the electorate (Hasell and Weeks, 2016), emphasizing the importance of these outlets in a broader political context.

Previous psychological literature has distinguished between high-arousal and low-arousal emotions, where high-arousal emotions are "associated with increased action readiness and behavioural activation" (Kraiss et al., 2023). Examples of high-arousal negative emotions are anger and fear, while low-arousal emotions include sadness or boredom. This action readiness has the potential to manifest into political action. Valentino et al built on this literature and studied the varied effects of different emotions on changes in political behaviour. Their analysis found that anger had the greatest impact on motivating political action, compared to anxiety and enthusiasm (Valentino et al., 2011). These findings, showing the strength of anger and other high-arousal emotions in motivating political participation, align with other studies, signaling a consensus in the research community (Weber, 2013) (Banks et al., 2019). Other papers discuss how politically driven anger can have consequences beyond voting behaviour and political support. When weaponized against groups like refugees, anger on social media has been associated with an increase in rates of hate crimes and prejudiced violence (Müller and Schwarz, 2020).

It is worth linking this research on emotions in politics back with the literature on the business models of born-digital news sites, as anger and anxiety have both been found to generally increase information sharing, further adding to the evidence that born-digital sites are advantaged from eliciting these emotions among their readers (Redlawsk and Mattes, 2022). This aligns with other research finding that tweets evoking anger about the 2011 German elections were widely retweeted (Stieglitz and Dang-Xuan, 2013). This literature demonstrates the importance of understanding what specific political discourse and information prompt high-arousal emotions from the general public. These emotions motivate political behaviour and could have a tangible impact on the UK's political system.

3 Research Questions and Hypotheses

Drawing motivation from gaps in past literature, the analysis in this paper will engage with several research questions.

RQ1: What types of emotional responses are observed following exposure to political news media?

H1: In the total survey population, regardless of treatment assignment, there will be mostly negative emotions with a reasonable number of neutral emotions.

RQ2: Are any demographic or political participant metadata associated with significant differences in observed emotional states following exposure to experimental stimuli?

H2: Participants who get the majority of their news from sources other than social media or blogs and participants who identify with left of center political parties will express more negative emotions and negative emotions of higher arousal levels. Participants who get the majority of their news from social media/blogs or participants identifying with right of center parties will express more neutral emotions.

There has been very little research dedicated to understanding how the emotions of individual consumers are impacted by exposure to political media. The first two research questions will therefore be explored by a descriptive analysis of overall observed emotions and entire-sample demographic differences in emotional responses. Research question 1 will engage with broad themes of emotions in politics and look at what type of emotional responses are observed following exposure to political media, regardless of whether participants were shown born-digital or legacy media. According to the literature's assessment of the media's ability to shape views and individual behaviour, it is likely that news also impacts emotions. Due to the negative framing of all articles included in the survey, we might expect the majority of expressed emotions to be negative. Despite this, it is possible that some participants may not feel impacted by the articles, resulting in neutral emotions.

Research question 2 will investigate whether we observe any differences in the demographics of participants who express certain emotions following exposure to either stimuli. It is possible that repeated exposure to sensationalist news on blogs or social media may result in desensitization of these participants to the emotional stimuli, meaning more neutral emotional responses (Brockmyer, 2012). Due to their political views, it is also likely that participants identifying closely with left of center parties will respond negatively to the stories that are critical of previous Conservative governments.

RQ3: When controlling for demographic and political metadata, are utterances produced by participants who were exposed to negatively framed articles in the style of born-digital media more likely to contain negative emotions, compared to utterances produced by those who were exposed to negatively framed articles in the style of legacy media?

H3: Utterances produced by participants in the style of born-digital news will be more likely to be negative in emotion.

RQ4: When controlling for demographic and political metadata, are utterances produced by participants who were exposed to negatively framed articles in the style of born-digital media more likely to contain high-arousal negative emotions, compared to utterances produced by those who were exposed to negatively framed articles in the style of legacy media?

H4: Utterances produced by participants in the style of born-digital news will be more likely to contain high-arousal negative emotions.

Research questions 3 and 4 will move beyond descriptive analysis and engage with the study's treatment design to focus on the main question posed in this paper – whether exposure to born-digital media produces more negative emotions and whether those emotions can be labelled 'high-arousal' in nature. From the literature discussed in Chapter 2 that touched on the type of content likely produced by born-digital media sites in the interest of shareability, it is expected that participants exposed to this type of news would express greater degrees of overall negative and high-arousal negative emotions.

4 Data and Methods

4.1 Content Analysis of News Articles

To design research that effectively studies differences between born-digital and legacy media, especially one involving participant exposure to this media, it is vital that the content typically published by both outlet types is well-understood. Despite the existence of theories derived from an extensive body of literature, a content analysis allows for the qualitative anchoring of theories and a better understanding of the typical axes of difference between born-digital and legacy outlets (Palmer, 2021). To analyse 6 months of media coverage, outlets were randomly selected from an exhaustive list of major media producers in the UK. The Guardian, Daily Mail, The Times, The Telegraph and The Metro comprised the legacy outlets, while Guido Fawkes, HuffPost, Politics Home, The Canary, and Politico UK made up the born-digital outlets.

Due to the cyclical nature of news, a simple random sample is not sufficient to obtain articles that are representative of media over time (Hester and Dougall, 2007). Instead, a two-constructed-week sample was used by randomly selecting two dates for each day of the week across a 6 month period. All articles published on these dates were gathered from the randomly selected outlets, and a subset of these were analysed to uncover typical axes of difference between the outlet types. Evidence suggests this technique gives an efficient and accurate sample that is representative of 6 months of media coverage (Hester and Dougall, 2007). The results of this content analysis can be seen below in Table 1:

Table 1: Counts of Articles in Each Qualitative Category

Category	**Born-Digital Articles**	**Legacy Articles**
Contains emotionally charged language	41	13
Does not contain emotionally charged language	30	59
Focus on personality side of politics	33	12
Focus on policy side of politics	38	60
Negatively framed	40	28
Neutrally framed	29	39
Positively framed	2	5
Objective journalism	35	58
Contains high levels of subjectivity	36	14

As seen above, born-digital articles contain higher degrees of emotionally charged language, as well as a greater focus on the personality side of politics rather than policy. There were also observed differences in framing, with born-digital outlets tending to present stories in a more negative light, while also involving higher levels of objectivity in their journalism. This content analysis reinforces the arguments proposed by previous authors in Chapter 2, but also helps guide the design of the data collection techniques for this paper's analysis.

4.2 Survey Methodology

Data for this paper's analysis was collected by recruiting UK-based respondents to answer a brief survey. Respondents were randomly assigned to one of two groups, one group read two articles in the style of a born-digital outlet while the other group read two articles in the style of a legacy media outlet. To obtain articles for the survey, information derived from the content analysis discussed in the section above was fed into a Large Language Model (Chat GPT-4); the model was asked to consider the findings and generate 4 articles, two in the style of each outlet type. Both articles in each group discussed identical topics, the Partygate scandal and waiting times in the National Health Service. Using this generation technique allows the articles to vary only in their journalistic style, while covering identical events and topics. The articles generated by the Large Language Model were manually reviewed, ensuring topical consistency and accuracy, similarity to expected journalistic style, and truthfulness. Appendix A shows the text contained in each article.

After reading each article, participants were asked to submit a brief audio recording, where they discussed their thoughts about the political topic covered in the article. Participant metadata was collected alongside these recordings, including age, gender identity, political party affiliation, and information about their typical political news consumption. See Table 2 below for summary statistics of participants in this study:

Table 2: Frequency Distribution Table of Demographic Variables

Category	**Count**
Age	
18-24	31
25-34	14
35-44	3
45-54	1

Category	**Count**
55-64	1
65-74	2
Gender	
Female	29
Male	23
Highest Level of Education	
No formal qualifications	1
Below degree level	5
Undergraduate degree	30
Postgraduate certificate or diploma	1
Postgraduate degree	15
How Closely Respondent Follows Political News	
Not closely at all	6
Not very closely	7
Somewhat closely	23
Very closely	15
Where Respondent Gets Majority of Political News	
Online newspaper or magazine	22
Social media	13
Television	4
Blogs or online forums	2
Podcasts	5
None/Doesn't follow news	1
Other	4
Political Party Respondent Identifies Most With	
Labour	11
Conservative	2
Liberal Democrats	11
Green Party	8
Other	4

Category	**Count**
Not close to any party	15

Table 2 shows that the sample obtained from the survey is heavily skewed towards younger, more educated participants. There is also a heavy imbalance in their political affiliation, with the Conservative Party significantly underrepresented, and the Green Party and Liberal Democrats quite overrepresented. Note that the survey included options for a range of regional political parties, but due to very small counts, these have been combined into an 'other' category.

4.3 Use of Audio Data

This data collection technique allows for the utilization of a novel analytical methodology, as introduced by Knox and Lucas in their 2019 paper, *A Dynamic Model of Speech for the Social Sciences* (Knox and Lucas, 2019). It involves using computational methods to classify utterances from speech clips into distinct emotional categories. While the analysis technique has previously been used with pre-existing audio data, to knowledge, this is the first time that the methods have been extrapolated for use in a paper relying on primary data.

The vast majority of previous studies rely on one of two methods for estimating the emotional states of participants, either self-reporting or textual cues. Self-reporting poses risks to the internal validity of studies, due to the potential for participants to express socially desirable views that may not align with their true feelings. Previous research shows that even in anonymous surveys, participants often shape their responses to align with views that are deemed culturally or socially acceptable (King and Bruner, 2000). Due to the strong normative influence in political settings, analysis similar to the one in this paper could be susceptible to greater degrees of skew due to participants aiming to adhere to political correctness (Mallinson and Hatemi, 2018). There are additional validity concerns arising from self-reported measures of emotion due to self-perception bias, where participants have a poor understanding of their own emotions (Dunning et al., 2004). Estimates relying on textual data, while likely more accurate than self-reporting, discard a great deal of data, namely the auditory features of a participant's speech (Acheampong et al., 2021). That is, these studies consider only what is said, not the manner in which it is said. The analytical techniques used in this paper aim to mark a departure from these methods, working towards a more accurate assessment of emotions in experimental and observational research.

After collecting audio files from the survey, a silence detection algorithm was used to trim the longer responses into utterances, or continuous trimmings of speech. Segmenting these audio files into utterances allows for the possibility that a participant's emotional state shifts over the time of speaking, likely giving a better representation of their overall feelings (Knox and Lucas, 2019). The minimum length of silence to split clips was 900 milliseconds; following trimming, a sample of utterances were manually inspected in order to verify the efficacy of the splitting. Features of each utterance were then extracted and turned into a time-sequential matrix object, where each column represents a unique auditory feature, and each row is a 25 millisecond frame in which the features are incrementally measured. 81 features that are associated with known linguistic differences in emotional states are used in the analysis of this paper, including energy, pitch, Mel-frequency cepstral coefficients, and a variety of formants. These features have been considered by past scholars to be robust in mapping speech audio (Darch et al., 2005) (Knox and Lucas, 2019).

It is worth highlighting the ethical and privacy risks associated with this type of data collection, especially with the emergence of powerful AI tools and threats from deepfake audio technology. Future researchers should be cautioned to always adhere to ethical best practices, especially relating to the storage of audio files collected from survey participants. The data collected in this paper was stored securely and made available to nobody external to the research project. All other ethical best practices were followed, including informed consent and assessing the potential risk for survey participants, and the project was given ethical approval by LSE's Research Ethics Committee.

4.4 Modelling Technique

Hidden Markov models (HMMs) can be used to assess the similarity between audio segments collected via the survey and utterances that have been hand labelled into emotional categories to train the models (Nwe et al., 2003). This training data consisted of a subset of the Crowd Sourced Emotional Multimodal Actors Dataset (CREMA-D), containing 7,442 clips from 91 voice actors of varying genders, ages, and ethnicities. The actors were recorded saying a range of different sentences, using different emotions (anger, disgust, fear, joy, neutral, and sadness) as well as different intensities of these emotions (Cao et al., 2014). Knowledge of the specific emotions being expressed by these actors allowed for the categorization of training utterances into the emotional states of interest for the purposes of this paper, namely high-arousal negative emotions (anger and fear), low-arousal negative emotions (sadness and disgust), and neutral or positive emotions (neutrality and joy). A qualitative listen to a subset of this data demonstrates that it robustly captures natural expressions of the expected emotions.

Initially, the audio features of these training clips were extracted for every 25 milliseconds, as discussed above. Separate hidden Markov models were then trained for each emotional category in the study. We will represent these mode-specific models notationally with λ_m. Training each HMM on just one category of emotions allows the models to learn the auditory features of the emotion and generalize parameters (θ) from the data generating the model (Knox and Lucas, 2019). Contained within the auditory parameters is the mean of each of the 81 features in the data (μ), a covariance matrix of features (Σ), and transition probabilities between model states (Γ) (Knox and Lucas, 2019). Previous research involving classification of speech using HMMs found that the number of states in each model ($nstates$) should map well to the number of phonemes in the audio generating each model (Nwe et al., 2003). Using this theory as a starting point, a range of possible values were iterated over, using a 5-fold cross-validation technique to grid search for the value yielding the best accuracy on validation subsets of CREMA-D audio files. Using the number of states that yielded the best performance, a similar grid search was performed over values of a regularization parameter, to prevent overfitting on the training data. Once again, the value yielding the best predictions was chosen for the final model. This hyperparameter tuning process was done for all three models containing each mode of speech.

Once the ideal hyperparameters were identified, each utterance (U_i) from the audio collected via the survey can be categorized into these three modes of speech (M), where each mode represents an emotional category. Following the training of three optimized HMMs using the cross-validated nstates and regularization parameter values, the models can be applied to each new utterance in the survey data to generate three log-likelihood values, capturing how similar the auditory features are in the test audio to the training utterances contained in each model (Rabiner and Juang, 1993). In other words, it demonstrates how similar this new data is to the audio expressing known high-arousal negative emotions, low-arousal negative emotions, and neutral or positive emotions. This allows for the comparison of log-likelihood values, where the model generating the maximum value for each utterance can be considered the closest auditory match (Rabiner and Juang, 1993). This is the mode of speech into which U_i will be classified. Note that survey utterance audio features were standardized to the mean and standard deviation of the models prior to calculating log-likelihood values, in order to remove any recording device discrepancies that could influence outcomes (Knox and Lucas, 2019). The log-likelihood maximization process is shown notationally in Equation 1 below:

$$M_u = \text{argmax} \log \left[P \left(U_i \mid \lambda_m, \theta_m \right) \right] \tag{1}$$

Following the classification of survey utterances into the emotional categories of interest using the hidden Markov models and comparative log-likelihood approach, tests for statistical significance in difference of proportions can be used to establish any inter-demographic patterns in the observed emotions, regardless of treatment assignment. A regression technique will then be used to establish whether there is any significant association between the treatment and outcome variable (emotional category classification). The predicted emotion variable will be one-hot encoded to get three separate dummy outcome variables capturing each of the emotions; three regression models will be run with each of these variables as the outcome in one model.

Initially, these models will be run with only the treatment assignment as an explanatory variable, allowing us to view the direct relationship between treatment and observed emotional state. The same models will then be re-run, this time including the participant metadata to control for differences in observable demographic and political characteristics. One specific concern is whether the age skew of the data will mean that the study population will have a greater than average exposure to born-digital or sensationalist blog-style media in their everyday lives (Davies, 2023). This could spur desensitization to the treatment in the born-digital group, perhaps leading to dampened or more neutral responses to the stimuli. The collection of metadata capturing age and where the participant gets the majority of their political news should help to mitigate this concern, as the data can be included in the regression models as control variables. In an experiment with randomized treatment assignment and a large number of participants, the need to control for pre-treatment covariates is dampened; however, small sample size could introduce random imbalance in observable characteristics, making these controls necessary for the purposes of this capstone project (Nguyen et al., 2017).

Previous pieces of research using HMMs as audio classifiers have generally focused on making within-subject classifications. For example, Knox and Lucas differentiate skeptical speech from neutral speech in United States Supreme Court deliberations by training 16 models, one per mode of speech per justice in their corpus. While this method may achieve greater classification accuracy due to the complete standardization of voices in each model (Rabiner and Juang, 1993), including a range of voices when training each HMM enables the methods used in this paper to be substantially more applicable to settings where researchers are attempting to uncover the emotional states of many people (Pulatov et al., 2023). This paper therefore marks a departure from previously used methods, showing a potentially innovative path forward in emotion recognition. Due to the novelty of these methods, the discussion later in this paper will go beyond engaging with the topical research questions outlined in the previous chapter by also reflecting on the utility of this methodological extrapolation. It will also comment on how future researchers can attempt to improve on the classification accuracy of generalizable audio emotion classifiers.

5 Analysis and Results

5.1 Hidden Markov Model Predictions and Performance

The cross-validation technique described in the methodology section of this paper indicated that the ideal number of states was 15 and that the inclusion of a regularization hyperparameter actually detracted from the accuracy of the models. Three optimized models were then trained, which correctly predicted the emotional categories of CREMA-D validation data approximately 55% of the time. It is worth noting that models in the paper by Knox and Lucas, using a similar methodology, achieved an accuracy of 68% for a binary classification problem. Relative to a baseline of random labels (50% for Knox and Lucas and 33% in this paper), this means that the models in this paper perform more favorably than those of other published works (66.7% improvement in this paper relative to randomness, compared to 36% for Knox and Lucas). This may be attributable to the high degree of auditory nuance in the emotions analysed by Knox and Lucas, compared to reasonably more distinct ones in this paper; however, this should provide some validity to the efficacy of the methodology in this capstone project. Note that this accuracy figure and the validity of these methods will be discussed in much greater detail in the subsequent chapter. The overall number of utterances that were classified into high-arousal negative, low-arousal negative, and neutral or positive emotions can be seen in Table 3 below:

Table 3: Total number of utterances in each category

High-Arousal Negative	**Low-Arousal Negative**	**Neutral or Positive**
219 *(0.39)*	238 *(0.43)*	99 *(0.18)*

As anticipated due to the negative framing of the news stories including in the survey, the vast majority of utterances were negative. 82.19% of all utterances were either high-arousal negative or low-arousal negative. Low-arousal negative emotions were the most prevalent among all survey participants, regardless of treatment assignment, followed quite closely by high-arousal negative emotions. There did appear to be some utterances that were neutral or positive, potentially due to disinterest or a lack of opinions about the political topic covered in the articles. These findings give evidence to support Hypothesis 1 and indicate that participants very often express negative emotions following exposure to a negative political news article.

5.2 Descriptive Metadata Analysis

The novelty of the methods used in this paper provides an opportunity for descriptive analysis of the demographics and politics of individuals producing utterances of certain emotions. Where provided by participants, the collection of age, gender, educational background, levels of political attention and political party affiliation as participant metadata made this analysis possible. See Table 4 below for counts of utterances in each emotional category by demographic, as well as proportions of utterances in each category for that demographic group:

Table 4: Utterances in Emotional Categories by Demographic

Demographic	**High-Arousal Negative**	**Low-Arousal Negative**	**Neutral or Positive**
Age			
18-24	135 *(0.39)*	147 *(0.43)*	60 *(0.18)*
25-34	62 *(0.39)*	65 *(0.41)*	31 *(0.20)*
35-44	1 *(0.08)*	12 *(0.92)*	0 *(0.00)*
45-54	5 *(1.00)*	0 *(0.00)*	0 *(0.00)*

Demographic	High-Arousal Negative	Low-Arousal Negative	Neutral or Positive
55-64	5 *(0.42)*	4 *(0.33)*	3 *(0.25)*
65-74	11 *(0.42)*	10 *(0.38)*	5 *(0.19)*
Gender			
Female	117 *(0.39)*	139 *(0.46)*	41 *(0.14)*
Male	102 *(0.39)*	99 *(0.38)*	58 *(0.22)*
Highest Level of Education			
No formal qualifications	3 *(0.60)*	1 *(0.20)*	1 *(0.20)*
Below degree level	22 *(0.41)*	25 *(0.46)*	7 *(0.13)*
Undergraduate degree	155 *(0.46)*	119 *(0.35)*	62 *(0.18)*
Postgraduate certificate or diploma	0 *(0.00)*	2 *(1.00)*	0 *(0.00)*
Postgraduate degree	39 *(0.25)*	91 *(0.57)*	29 *(0.18)*
How Closely Respondent Follows Political News			
Not closely at all	16 *(0.24)*	45 *(0.68)*	5 *(0.08)*
Not very closely	21 *(0.29)*	47 *(0.64)*	5 *(0.07)*
Somewhat closely	117 *(0.46)*	100 *(0.39)*	40 *(0.16)*
Very closely	63 *(0.45)*	46 *(0.33)*	31 *(0.22)*
Where Respondent Gets Majority of Political News			
Online newspaper or magazine	102 *(0.42)*	87 *(0.36)*	56 *(0.23)*
Social media	71 *(0.41)*	76 *(0.44)*	27 *(0.16)*
Television	10 *(0.21)*	27 *(0.56)*	11 *(0.23)*
Blogs or online forums	6 *(0.55)*	4 *(0.36)*	1 *(0.09)*
Podcasts	21 *(0.62)*	9 *(0.26)*	4 *(0.12)*
None/Doesn't follow news	5 *(1.00)*	0 *(0.00)*	0 *(0.00)*
Other	2 *(0.05)*	35 *(0.95)*	0 *(0.00)*
Political Party Respondent Identifies Most With			
Labour	50 *(0.53)*	28 *(0.30)*	16 *(0.17)*
Conservative	11 *(0.37)*	11 *(0.37)*	8 *(0.27)*
Liberal Democrats	37 *(0.32)*	47 *(0.41)*	31 *(0.29)*

Demographic	High-Arousal Negative	Low-Arousal Negative	Neutral or Positive
Green Party	40 *(0.40)*	48 *(0.48)*	12 *(0.12)*
Other	10 *(0.28)*	19 *(0.53)*	7 *(0.19)*
Not close to any party	70 *(0.40)*	79 *(0.46)*	25 *(0.15)*

The summary statistics in Table 4 above motivate hypothesis testing, allowing us to determine if certain observed differences in proportions are statistically significant. There particularly appear to be demographic differences in the arousal levels among the negative utterances produced by participants in this study. It appears that the negative utterances produced by respondents with a postgraduate degree and those with other levels of education are substantially different in their arousal levels. A two-sample Z-test for equality of proportions shows that there is a statistically significant difference between the arousal levels of their negative utterances, and that respondents with a postgraduate degree show significantly lower propensity of displaying high-arousal negative emotions than those with less education (p-value = 5.928e-07). Unfortunately, small counts in the lower education categories prohibit us from comparing undergraduates or postgraduates to those with no formal education; however, we can show that this significant difference exists even between utterances produced by undergraduate and postgraduate participants.

Additionally, the arousal level of negative utterances appears to be associated with a participant's level of attentiveness to political news. When collapsed into a binary variable capturing whether or not a respondent tends to follow political news, a two-sample Z-test is once again statistically significant, showing that respondents paying close attention to political news produced elevated proportions of high-arousal levels in their negative utterances (p-value = 3.272e-07).

Lastly, relative to supporters of other political parties, negative utterances produced by supporters of the Labour party also appear to be frequently higher in arousal. Once again, when using a two-sample Z-test comparing utterances produced by participants who identify with the Labour party and utterances from participants who identify with other UK parties or no party at all, the result is statistically significant at alpha = 0.05 (p-value = 0.002).

Moving away from differences in the arousal levels of negative utterances, it also appears as though utterances from participants identifying most closely with the Liberal Democrats were more likely to be neutral or positive than the utterances of the other respondents. A two-sample Z-test is significant for a difference in the proportion of total utterances that are neutral or positive from Liberal Democrat participants and the rest of the participants (p-value = 0.005). This could, in theory, be due to the history of the Liberal Democrats as a more centrist, big tent party, adopting stances from the center-left and center-right of the political spectrum. Having said that, the Liberal Democrats have become a more progressive party in recent years (Thun, 2024), and this result may stand out as one that is somewhat unexpected.

The findings of this descriptive analysis show evidence both supporting and in opposition to parts of Hypothesis 2. Data showing that negative utterances from Labour supporters have higher levels of arousal supports the expectation that participants identifying with left-of-center parties will express more high-arousal negative emotions; however, the Liberal Democrat supporters showing an increased degree of neutral or positive emotions contradicts it. At the same time, due to very few respondents supporting the Conservative party, we cannot conclude that participants identifying with right-of-center parties express more neutral or positive emotions. This again does not support Hypothesis 2. Similarly, there is not sufficient evidence to conclude that respondents receiving the majority of their news from social media or online blogs express more neutral emotions or that respondents receiving their news from sources other than social media and blogs express more negative and high-arousal negative emotions. Fixing the issue of small counts in these categories would allow for a more robust testing of this hypothesis.

5.3 Association Between Treatment and Predicted Emotions

A regression approach can be used to determine whether treatment assignment is associated with differences in emotions. Initially, regression models were run with only the treatment as an explanatory variable, allowing us to look at the direct relationship between treatment and outcome. See Table 5, Table 6, and Table 7 below for the results of these regression models.

Table 5: Logistic Regression Model for High-Arousal Negative Dummy Variable

	Estimate	**Std. Error**	**Z Value**	**Pr($>\mid Z \mid$)**
Intercept	-0.405	0.121	-3.353	0.001
Born-Digital Treatment	-0.053	0.174	-0.303	0.762

Table 6: Logistic Regression Model for Low-Arousal Negative Dummy Variable

	Estimate	**Std. Error**	**Z Value**	**Pr(>| Z |)**
Intercept	-0.362	0.120	-3.005	0.002
Born-Digital Treatment	0.147	0.172	0.857	0.392

Table 7: Logistic Regression Model for Neutral/Positive Dummy Variable

	Estimate	**Std. Error**	**Z Value**	**Pr(>| Z |)**
Intercept	-1.453	0.151	-9.616	2e-16
Born-Digital Treatment	-0.160	0.223	-0.721	0.471

From the tables above, it appears that being in the born-digital treatment group is associated with a slight decrease in the odds of expressing high-arousal negative emotions or neutral/positive emotions. An utterance being produced by a participant in the born-digital group is associated with an increase in the odds of that utterance containing low-arousal negative emotions. However, it is important to note that all of these point estimates are insignificant at $\alpha = 0.05$ and $\alpha = 0.10$.

Due to the small number of participants in this study, it is highly likely that there is randomly induced imbalance of pre-treatment covariates that could, in theory, be associated with both treatment effect and expression of emotions. This makes it crucial that models are also run including demographic metadata (age, education level, gender) and political metadata (party affiliation, how closely participant follows politics, and main source of political news). After controlling for all of these factors, the new point estimates and significance levels can be seen in Table 8, Table 9, and Table 10 below:

Table 8: Logistic Regression Model for High-Arousal Negative Dummy Variable (With Controls)

	Estimate	**Std. Error**	**Z Value**	**Pr(>| Z |)**
Intercept	-0.791	1.363	0.580	0.562
Born-Digital Treatment	-0.383	0.254	-1.504	0.133

Table 9: Logistic Regression Model for Low-Arousal Negative Dummy Variable (With Controls)

	Estimate	**Std. Error**	**Z Value**	**Pr(>| Z |)**
Intercept	0.454	1.404	0.323	0.747
Born-Digital Treatment	0.383	0.265	1.444	0.149

Table 10: Logistic Regression Model for Neutral/Positive Dummy Variable (With Controls)

	Estimate	**Std. Error**	**Z Value**	**Pr(>| Z |)**
Intercept	-17.231	1615.104	-0.011	0.992
Born-Digital Treatment	0.280	0.321	0.870	0.384

After controlling for the participant metadata, utterances produced by participants in the born-digital treatment group are slightly less likely to be of high-arousal negative emotions than utterances produced by participants in the legacy media treatment group. Conversely, born-digital utterances are slightly more likely to be of low-arousal negative emotions than legacy utterances. Finally, and perhaps most surprisingly, born-digital utterances are slightly more likely to be neutral or positive than legacy utterances. All of these results are still statistically insignificant at both $\alpha = 0.05$ and $\alpha = 0.10$; however, the p-values of 0.133 and 0.149 from the high-arousal negative and low-arousal negative dummy models indicate near significance. Despite not meeting the conventional threshold, these results still appear meaningful to the field of study (Abadie, 2020), especially given that the alpha level is often allowed to rise to between 0.1 and 0.2 in exploratory studies such as this one (Serdar et al., 2021). These findings appear to go directly in contrast to Hypothesis 3 and Hypothesis 4, assuming the results have not occurred by chance. Further investigation is required to identify the mechanism driving the outcome as well as the significance of the relationship seen in this study.

6 Discussion

6.1 Real-World Implications of Results

While this paper aims to study the impact of political media on the emotional states of consumers, it is also important to mention how these results add to our understanding of British politics on a whole. We can note widely studied sociopolitical trends and identify how the findings in this paper could support or challenge them. By linking these findings back to the studies discussed in the literature review, we can further demonstrate how this paper builds on the corpus of existing work in a meaningful way.

One of the primary motivations driving the research questions that were posed in this paper is due to the literature's suggestion that high-arousal negative emotions in media could be linked to shifts in behaviour (Valentino et al., 2011). This demonstrates the importance of understanding how frequently these emotions are currently being seen among readers of political news. Perhaps, then, one of the most meaningful findings is that in response to negatively framed articles, the respondents in this study overwhelmingly reacted in a negative way, and nearly 40% of participant utterances contained high-arousal emotions. This strongly suggests that political articles are often able to shape the emotions of UK residents, at least temporarily, and emphasizes the utility of politicians relying on the media as vehicles for delivering emotional content to the public. It is important to note that we cannot causally attribute these negative emotions to the articles, due to a lack of control setting where participants are exposed to neutral or positively framed articles; however, this finding is suggestive of a strong association and warrants further attention. Considering the past literature describing action readiness potential in high-arousal emotions, this finding could also indicate that exposing the public to similarly negative media immediately prior to an election could spark short-term behavioural change.

This literature also motivates us to understand the typology of a voter that is more likely to respond emotionally to media in this way. Findings could point to heightened levels of action readiness among certain populations that may result in a tangible impact on politics. For instance, showing that respondents with a postgraduate degree often respond in a lower-arousal manner points to the possibility that those with lower levels of educational attainment are more susceptible to behaviour-inducing emotions following exposure to media. This finding in the context of steadily increasing postgraduate enrollments may prompt political actors to reframe their emotional appeals in a bespoke manner for areas correlated with higher or lower average levels of education. Similarly, the increase in high-arousal negative emotions produced by respondents who reported greater levels of political attentiveness could motivate politicians to push for greater political education and awareness.

The link between producing utterances expressing high-arousal negative emotions like anger and fear and reporting support for the Labour party could be due to a wide range of mechanisms. To briefly contextualize this research, the data collection process took place immediately prior to a general election. These participants were thus likely exposed to Conservative-critical messaging from the party before their participation in the study, potentially heightening the effects of the survey stimuli that disapproved of the Conservative Government. We can only hypothesize why this increase may have happened and leave it to future scholars to explore; that question is outside of this paper's scope. What may be more uncertain is the reason for utterances produced by Liberal Democrat supporters more often being neutral or positive than the rest of the respondents. This could, in theory be indicative of the Liberal Democrats having appeal as a big tent party, but as previously said, further data would be required to understand the reason for this observation.

Aside from using this unique methodology to uncover patterns related to the demographics and politics of the respondents, a large portion of the analysis was focused on testing hypotheses about differing responses to born-digital media compared to legacy media. Despite the extensive theoretical backing and content analysis demonstrating the sensationalist media produced by born-digital outlets, when controlling for participant metadata, there was a slight decrease in the likelihood of observing high-arousal negative emotions, compared to utterances produced by participants in the legacy media group. As previously mentioned, this result does not meet the historic threshold for statistical significance with a p-value of 0.05; however, its near significance (p-value = 0.13) could indicate meaningfulness, especially in a pilot study (Serdar et al., 2021). At the very least, it invites further investigation.

If this result is indeed meaningful and the point estimate accurate, it could signal a variety of implications about both media and politics. For one, if born-digital outlets rely on eliciting greater degrees of high-arousal emotions than their competitors, the results in this paper could signal trouble for these publications. As discussed in the literature review, past work has strongly linked high-arousal emotions to shareability of media, which online-only publications require to survive in the ever-growing media environment (Berger and Milkman, 2012). If born-digital publications do in fact struggle to induce these emotions among their readers, there could be a large number of publications placed in a financially precarious position. This could signal a shift in the overall environment of political media in the UK.

Similarly to the demographic findings, we can only hypothesize the reasons that legacy outlets appear to prompt more high-arousal negative emotions than born-digital outlets. Due to recent efforts aiming to educate the public about biased media and misinformation, it is possible that sensationalist publications are viewed as less trustworthy and thus warrant a milder response among participants (van der Meer and Brosius, 2024). Van der Meer and Brosius argue in their 2024 paper that when news contains sensationalist aspects or becomes too negative in nature, it is likely that readers become more skeptical. In this context of this finding, the results seen in this analysis seem plausible, and it is possible that born-digital outlets do not in fact produce greater levels of high-arousal negative emotions. On the other hand, if legacy media is deemed more trustworthy, information aligning with pre-existing beliefs that is critical of a commonly disliked politician could prompt anger. These findings should undoubtedly invite further study into the topic.

6.2 Limitations of Analysis

Despite its good performance relative to other HMM-based classifiers seen in past papers, the most obvious limitation of this paper is its classification accuracy. As the conclusions drawn from the experimental design rely on the accuracy of emotional category classifications, the findings in this paper must be taken with a reasonable degree of caution. Due to the inaccuracy of the modelling technique, we should also be skeptical about fully endorsing the methods from this paper unless they can be substantially improved on to achieve a degree of accuracy that is more suitable for classification tasks. The use of Hidden Markov Models may still be ideal for use in circumstances where researchers aim to reveal emotional states from much larger corpuses of audio data. In this instance, HMMs are able to provide computationally cheap ways of factoring tone into a machine learning classifier. Perhaps the most suitable path forward is a modelling technique that combines textual cues with auditory features (Chou et al., 2023). Improving on the classification performance of these methods will provide a challenge to future researchers but should not be shied away from, due to their potential to provide unique insights into emotional states in experiments with large numbers of participants.

It is also extremely important to mention that the small sample size in the survey limits the generalizability of the findings. While the audio files from the survey were split into more than 550 utterances, these clips only came from 52 participants. It is extremely difficult to assume that the results in this paper would be the same given a different or indeed larger, more representative survey population. This sample size also resulted in many small counts in levels of categorical variables, placing a restriction on our ability to establish certain patterns, or lack thereof, within the data. While findings in this paper remain useful in drawing preliminary conclusions about the impact of media types on voters, other researchers should perform a similar analysis with a larger survey population to test the robustness of these results. Due to funding and time constraints, that was not possible to do in this capstone project.

Lastly, it is possible that using CREMA-D as training data was not ideal for a classification task of British English speakers, given that the audio contained only North American voices. CREMA-D was selected as training data due to its diversity in ethnicity and gender as well as having comprehensive emotion labels and allowing for variety in intensity of emotions. The impracticalities of collecting primary data in the form of thousands of emotion-specific speech utterances from British actors mean that CREMA-D was likely the best training data available for the purposes of this project. Having said that, slight linguistic differences in American and British accents may have led to nuanced dissimilarities in the audio features extracted in the training and survey data (Lindsey, 2015). This could, in theory, mean that a small amount of accuracy was sacrificed in the modelling process. Given the large number of features for each audio file that is included in the analysis, any lost accuracy would likely be of a very small degree, but future researchers may consider, wherever possible, utilizing training data that is a closer linguistic match to their population of study.

6.3 Directions for Future Research

Future researchers should consider exploring a variety of directions that would improve on this piece of research. Firstly, as briefly discussed above, designing an ensemble methods modelling technique that considers both tone and words through the use of text and audio data would allow researchers to combine aspects of proven techniques and potentially achieve greater degrees of classification accuracy. A key challenge will be in determining how much each data format should contribute to emotional state predictions (Chou et al., 2023). Given the complexity of this technique, requiring the processing of large amounts of audio and text, there may also be computational challenges present to researchers. It might also be worth considering improving on audio-only emotion classifiers by using ensemble methods to combine Hidden Markov Modelling techniques with neural network based classifiers (Akinpelu and Viriri, 2023). This could also present similar computational challenges to the audio-textual model.

Methodological scholars might further compare the utility of HMM-based emotion classifiers in different research settings, testing whether the technique may be more applicable in some studies and less so in others. It was mentioned in the Data and Methods chapter that past scholars often focused on classifying speech from small numbers of people and training separate models for every emotional state and individual in the study. In survey research such as this paper, that would be impractical and too computationally demanding. It might therefore be useful for one group of researchers to run two topically identical and methodologically related HMM-based studies alongside each other, changing only the size and scale of the research. They could perform one study with fewer participants, collecting enough data from each participant to train separate models for each individual. The other study would be identical to the techniques used in this paper, using training data from a large number of people. This allows for a generalizable modelling approach in survey research and the collection of less data from each participant. Testing whether HMMs perform better using training data that is linguistically identical to the test data while holding all other factors constant between the two studies could help identify whether HMMs are more useful in research for large-scale surveys or smaller scale focus group or interview-based studies. Scholars must also consider whether any increase in accuracy gained from training individual participant models outweighs the incurred computational costs.

To improve our understanding of emotional states resulting from media exposure, future work should also undertake a similar methodology and topical design to the one in this paper, with a greater number of survey participants. This will improve the validity of the results in this paper and test whether findings hold constant under a different and larger sample of UK residents. It will also allow for more robust testing of hypotheses and likely solve the issue of small counts in certain categories of pre-treatment covariates. It is possible that by scaling up the sample size, our results that approach significance could become more meaningful due to increased statistical power. Increasing the sample size will additionally allow for the better functioning of randomized treatment assignment by eliminating imbalance of demographic and political covariates between the experimental groups, thus minimizing the need to include controls in regression models.

Lastly, while this paper gives a useful indication of the emotional states of survey participants immediately following exposure to the stimuli, psychological research has shown that behavioural change is more motivated by lasting emotions (Gravert, 2020). Designing a similar study and including a longitudinal element could help researchers determine whether emotional responses seen in the results of this paper remain with participants over time. This would provide greater evidence that media has the ability to shape behavioural action in the long-term.

7 Conclusion

To recap, this paper found that when presented with negatively framed political news stories, most respondents reacted negatively, with a good proportion of utterances (0.39) displaying high arousal levels of negative emotions. It further noted demographic trends in observed emotions by highlighting groups within the data that displayed significantly greater propensities of certain emotions. Lastly, it analysed the relationship between outlet type and emotions, and showed that utterances produced by respondents assigned to the born-digital treatment group were associated with a decreased likelihood of being high arousal and negative (although this association did not meet the typical threshold for statistical significance). While this paper has uncovered insightful patterns in the data, we can only hypothesize about the mechanisms driving these results. Further investigation would be required to causally attribute any findings to media in particular. It has however engaged with past literature to infer why these relationships may have been present in the results, while challenging previously held hypotheses about the emotions prompted by born-digital outlets.

Methodologically, this paper has provided additional exploration of an analytical technique that remains very under-utilized. While it defends the use of these methods in certain circumstances, it has also invited an ongoing debate over the merits of choosing hidden Markov model-based classifiers over textual ones and has suggested an exploration of ensemble learning techniques that combine HMMs with either text-based approaches or audio neural network classifiers. It has also marked a departure from the previous uses of hidden Markov models by extrapolating the techniques for use with primary data and generalizable multiple-individual models. While this study has noteworthy limitations, the findings should undoubtedly prompt further investigation into the patterns noted in its analysis.

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Appendix A

Born-Digital Article 1: BoJo Under Fire: Partygate Scandal Rocks Downing Street with Explosive Revelations.

The Partygate scandal has sent shockwaves through the UK, with Boris Johnson facing mounting criticism over allegations of lockdown-breaching parties at Downing Street.

In an infuriating turn of events, a leaked video showing staff joking about a Christmas party during the strictest COVID-19 lockdown has gone viral, triggering public outrage. Social media is ablaze with condemnation, with many calling for Johnson's resignation. One Twitter user remarked, "This is an absolute disgrace. While we were stuck at home, they were partying. Boris has to go!"

The revelations have also fueled doubts over Johnson's credibility. Critics argue that the Prime Minister has lost touch with the realities faced by ordinary citizens.

Adding to the scandal, an insider report claims that these gatherings were frequent, further intensifying public fury. "It wasn't just a one-off; this was a pattern of behavior," the source revealed.

As the scandal unfolds, Johnson's approval ratings are plummeting. The opposition has seized the moment, with Labour leader Keir Starmer blasting Johnson's conduct in Parliament. "The Prime Minister's actions are a slap in the face to all who sacrificed during the pandemic," Starmer asserted.

Can Boris Johnson weather this storm, or is this the beginning of the end for his premiership?

Born-Digital Article 2: NHS in Crisis: Soaring Wait Times Leave Patients Desperate and Outraged

The National Health Service (NHS) is in shambles as wait times for treatments have surged, leaving millions of patients frustrated and in pain. Some are waiting months, or even years, for essential procedures, prompting public outrage.

Social media is awash with heartbreaking stories. One viral tweet read, "My mother has waited over a year for her hip replacement. She's in constant pain. This is unacceptable." These stories highlight the growing desperation among patients across the country.

Health experts warn of a looming disaster. "We're on the brink of a healthcare crisis," said Dr. Sarah Thompson, a healthcare analyst. "The backlog is unprecedented, and without immediate action, the consequences will be dire."

Facing fierce criticism, Prime Minister Boris Johnson announced a £5 billion emergency fund to tackle the issue. However, many argue that this is a temporary fix. "We need sustainable, long-term solutions," Dr. Thompson added.

Adding to the controversy, there are claims that the government has ignored repeated warnings about the growing crisis. Critics are blasting the Prime Minister for what they see as a lack of foresight and preparedness.

As the NHS struggles, public trust in the healthcare system is dwindling. Patients are left wondering when they will receive the care they desperately need, and whether the government's measures will be enough to restore faith in the beleaguered service.

Legacy Article 1: Boris Johnson Faces Inquiry Over Alleged Lockdown Parties at Downing Street

Prime Minister Boris Johnson is currently facing an inquiry into allegations of lockdown parties held at Downing Street during the height of the COVID-19 pandemic.

The controversy intensified following the release of a video in which Downing Street staff appear to be joking about a Christmas gathering that reportedly took place while lockdown measures were in effect.

The video, which surfaced on social media, has garnered a substantial reaction from the public. Many have expressed their dissatisfaction with the perceived double standards, given the strict lockdown regulations that were imposed on the general public at the time.

In Parliament, opposition leaders have been vocal in their criticism of the Prime Minister. Labour leader Keir Starmer has described the incident as "deeply troubling" and a "breach of public trust." He emphasised the importance of transparency and accountability in government.

An internal investigation led by senior civil servant Sue Gray is underway to ascertain the facts surrounding these gatherings. The investigation will look into whether any lockdown rules were breached and the extent of the involvement of senior officials, including the Prime Minister.

While the inquiry is expected to shed light on the events in question, the political fallout from this scandal continues to unfold, with many wondering how it will impact Boris Johnson's tenure as Prime Minister.

Legacy Article 2: Government Announces Measures to Address NHS Wait Times

The UK government has unveiled new measures aimed at tackling the increasing wait times within the National Health Service (NHS), following rising public concern over delays in medical treatment.

Recent data indicates that some patients face delays of several months to over a year, partly due to the impact of the COVID-19 pandemic and ongoing staffing shortages. These delays have contributed to growing public dissatisfaction.

Prime Minister Boris Johnson has pledged a £5 billion emergency fund to reduce waiting lists. "We understand the frustration and pain caused by these delays," Johnson stated. "This funding aims to provide immediate relief and support to the NHS." However, the allocation of this fund has been met with skepticism from various quarters.

Healthcare professionals have cautiously welcomed the announcement but stress the necessity of long-term solutions. Dr. Sarah Thompson, a healthcare analyst, commented, "While the emergency fund is a positive step, sustainable strategies, including increased staffing and improved infrastructure, are crucial for lasting improvements."

Opposition leaders have criticised the government's handling of the NHS crisis. Labour leader Keir Starmer called for a comprehensive plan to address the root causes of the delays, emphasising the need for adequate resources and sustained support for the NHS. "Short-term fixes will not resolve the systemic issues plaguing our healthcare system," Starmer noted.

As the NHS implements measures to reduce wait times, the focus remains on ensuring timely care and support for patients. The situation continues to evolve, with efforts ongoing to enhance the efficiency and effectiveness of the healthcare system. The public and healthcare professionals alike are watching closely to see if these measures will lead to meaningful change.

Appendix B - Acknowledgments

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