The following paper was researched and written as part of LSE GROUPS 2025.

LSE GROUPS takes place during the final fortnight of the LSE Spring Term. Undergraduate students are placed in small groups; these are cross-year, interdisciplinary, and group members do not know one another in advance. Each group must then devise its own research question and carry out every stage of a small-scale research project, in less than two weeks.

LSE GROUPS is part of the LSE commitment to students learning through enquiry and developing the skills needed for knowledge creation.

The overall theme of LSE GROUPS 2025 was *Visions for the Future*

This paper was submitted on the final Thursday afternoon of the project. Students then presented their work at a conference, on the closing Friday.

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London School of Economics and Political Science

From Tweets to Tomorrow: The Effectiveness of Reform UK's X Presence and Its Implications for Future UK Populist Electoral Strategy

Maya Townley, Jaiveer Singh Madan, Karam Khanna,
Wen Juin Ng, Quincy Jules Tan, Hanbing Chen

Abstract

In an age of digital communication and media consumption, the effectiveness of electoral strategy increasingly depends on how well parties interact with potential voters on online platforms. This study examines the activities of the right-wing populist party Reform UK on X (formerly Twitter), with a focus on its use of language and sentiment. Drawing on existing scholarship in sentiment analysis and political communication, this article explores the relationship between sentiment, user engagement, and voting intentions: an under-researched yet increasingly relevant area in light of the growing influence of right-wing populist parties worldwide. Performing sentiment analysis on over 1,300 posts by Reform UK on X, we evaluated the role of social media in the party's electoral strategy during the period between the 2024 general election and the 2025 local council elections. We tested the relationship between sentiment and engagement, engagement and voting intention, sentiment and voting intention, across different electoral periods. We then conducted a multi-group SEM to investigate a hypothesised partial or full mediation model of sentiment to voting intention via engagement. Our findings indicate that engagement partially mediates the relationship between sentiment and voting intention. Specifically, more negative sentiment drives higher engagement, which in turn slightly increases voting intention.

Keywords: Sentiment Analysis, Reform UK, Political Communication, Twitter, Electoral Strategy

1 Introduction

The 2025 UK local elections marked a significant political shift with Reform UK securing over 670 of the approximately 1,600 seats (Seddon, 2025). The party also led national opinion polls, polling 8% higher than Labour and 10% higher than the Conservatives (YouGov, 2025). Rising support for this new party illustrates a growing trend in contemporary politics: the strategic use of social media to engage and mobilise voters.

The increasing influence of social media on political communication and public opinion has also attracted considerable academic interest (Tsugawa Ohsaki, 2017; Tumasjan et al., 2010). Despite the extensive amount of literature, there remains limited information on the impact of social media sentiment on voter intentions within the context of UK politics.Understanding this relationship is essential to anticipating how future campaigns may adapt in an increasingly digital political environment, where strategic messaging is designed to provoke emotion, shape public opinion and counter their opposition.

This paper examines how sentiment expressed by Reform UK on X influenced user engagement and voting intention during the 2024 UK General and Local Elections. Through the use of sentiment analysis on tweets from the party's official account, we explored two key relationships: the impact of sentiment on engagement and the effect of engagement on voting intention. A multi-group Structural Equation Model (SEM) was used to test for mediation effects across different electoral contexts. Our findings offer new insights into how technopolitical strategies shape engagement and voting intentions in our digital era.

2 Literature Review

2.1 Social Media and Political Polarization

Political parties are increasingly using social media alongside traditional media to reach broader audiences, influence public opinion, and engage with voters in real time in comparison to traditional media campaigns alone (Paatelainen et al., 2022). Empirical studies have demonstrated that higher social media presence correlates with increased vote shares as voters become more exposed and engaged with the party's political messaging (Effing et al. 2012; Effing et al. 2016). Conover et al. (2012) highlight how right-learning networks on X enable rapid information diffusion and amplification of political messages. For instance, Trump's 2016 campaign notably utilised Twitter for direct communication, confrontation, and mobilisation, which strongly contributed to his political communication and mobilisation of support (Benkler et al., 2017; Buccoliero et al., 2020). X as a platform is widely used for analysis in political communication studies as it enables direct two-way interactions between individuals to share their thoughts and opinions on certain topics (Qi and Shabrina, 2023).

However, X's recommendation algorithm tends to amplify echo chambers by disproportionately promoting divisive content (Huszár et al., 2021; Skoric et al., 2021). Therefore, emotionally charged language is a core strategic element in digital political campaigns. According to Kubin and Von Sikorski (2021), social media contributes to political polarisation, primarily through selective exposure and active sharing (Cho et al., 2018; Johnson et al., 2020). This is often intensified by posts that evoke anger, fear, or pride, which drive higher engagement and more confrontational discourse. Such emotionally resonant messages can also translate into offline political action, including protests and demonstrations (Chang & Park, 2020).

2.2 Emotions, Sentiment, and Political Decisions

Emotion is a powerful driver of political communication. Tweets that elicit high emotional arousal - particularly anger, anxiety, and moral outrage - receive significantly greater engagement (Antypas, Preece & Camacho-Collados, 2023; Pivecka, Ratzinger & Florack, 2022). Tsugawa and Ohsaki (2017) found that negative tweets spread at least 20% more widely and quickly than positive or neutral ones, whilst Steiglitz and Dang-Xuan (2013) provide evidence of stronger retweeting for negatively charged content. Emotion's central role in influencing political judgement was shown by Conover and Feldman (1989), with recent research suggesting that emotionally framed political messages enhance credibility and engagement, particularly when confirming the user's pre-existing beliefs (Boukes, 2021; Stier et al., 2020).

Sentiment analysis, the computational identification of emotional tone in digital text (Liu, 2020), has become essential for understanding how sentiment influences engagement. Various tools have been employed in political contexts, such as SentiStrength (Steiglitz & Dang-Xuan, 2013), to assess the sentiment of politically relevant tweets from the 2011 German state elections, with more recent transformer-based models like DistillRoBERTa being used to assess Twitter data (Ramos & Chang, 2023). These studies highlight the importance of sentiment analysis tools in capturing the emotional dynamics of political communication in cyberspace.

2.3 Next Step

The paper aims to uncover how sentiment expressed by Reform UK on X affects voter intention through engagement. We do this by outlining our methodology, presenting our results, and discussing their implications. We focus on four main hypotheses:

H_1: Does negative sentiment increase engagement on X?

H_2: Does engagement increase voting intentions?

H_3: Does negative sentiment increase voting intentions?

H_4: Does sentiment on X impact voting intentions via engagement?

Reform UK was selected due to the lack of literature surrounding the party, as well as the party now being recognised as the main opposition to the current Labour Party (Skinner, 2025). Reform UK, originally founded as the Brexit Party in 2019, rebranded after the UK's EU withdrawal and repositioned itself as a populist in response to post-Brexit disillusionment, campaigning on themes of immigration control, cost-of-living concerns, and political transparency (Robaina, 2025). The party casts itself as a rational, outsider-led corrective to a corrupt political elite (Heath et al, 2024). Nigel Farage, the founder, is central to this branding, often portraying himself as the embodiment of anti-establishment defiance (Kelsey, 2015).

3 Methodology

3.1 Data Collection

Due to the discontinuation of X's public API in 2023, the team of researchers manually scraped all tweets from Reform UK's official account (`@reformparty_uk`) posted between 22 May 2024 (The 2024 General Election announcement) to 10 June 2025. For each tweet, we collected the tweet content and engagement metrics: likes, retweets, replies, and views. In total, 1490 tweets were retrieved.

Polling data on voting intention was also manually scraped from Politico's UK Poll of Polls, spanning the period from 22 May 2024 to 5 June 2025. After the data collection, the data have been cleaned and the cleaning process resulted in a final sample of 1388 tweets (Appendix for detailed information on how the data was cleaned).

3.2 Variable Construction

Following data cleaning, we constructed and standardised the variables in our regression and mediation models. These include sentiment, engagement, voting intention, and political periods.

3.2.1 Sentiment Score

Sentiment analysis was performed using a RoBERTa transformer model via the Hugging Face library (Wolf et al., 2020) using Python (version 3.12.7). Before analysis, tweets were preprocessed (removing extra spaces, special characters, and stop words). The preprocessed tweets were used to generate sentiment scores, ranging from -1 (most negative) to 1 (most positive), with 0 representing neutral sentiment.

3.2.2 Engagement Score

Engagement was conceptualised as a latent variable reflecting audience interaction with tweets. Three observed metrics - likes, retweets, and replies were extracted were each tweet and log-transformed to reduce skew and improve normality. A Confirmatory Factor Analysis (CFA) was conducted on the log-transformed metrics. While likes (loading = 0.988), retweets (0.962), and replies (0.821) demonstrated strong factor loadings onto the latent factor of engagement, views showed a lower loading (0.701) and substantially greater residual variance (0.359). Based on these CFA results, views were excluded from the final engagement construct as being less representative of active user engagement. The final engagement score (E) was calculated as the sum of three log-transformed metrics.

3.2.3 Voting Intention

Voting intention was operationalised as a continuous dependent variable measured as the percentage of respondents who reported that they would vote if a general election was held that day. Each tweet was matched to its corresponding polling day to align social media activity with public opinion data over time.

3.2.4 Election Period Classification

To account for variation in political context, we constructed a categorical variable identifying the campaign status in which each tweet was posted. Each Tweet was then matched with a period. The three distinct political periods that were identified are as follows:

- Period 1 - General Election Campaign (22 May - 4 July 2024)
- Period 2 - No Campaign (5 July 2024 - 15 April 2025)
- Period 3 - Local Election Campaign (16 April - 5 June 2025)

Each tweet was then assigned a value of 1, 2 or 3 depending on the date it was posted.

3.2.5 Control variables

Two variables were included as controls in all regression and mediation analyses:

- Date: The posting date of each tweet was recorded to account for different temporal variations in engagement or voting intentions.
- Views: The number of views per tweet was included to reflect how often a tweet was algorithmically exposed to users on X.

4 Results

To investigate the relationship between sentiment, engagement, and voting intention across different electoral contexts, we fit linear regression models to the data. More information on the models and their rationales can be found in the Appendix. Our analysis revealed several significant relationships between sentiment, engagement, and voting intention across different electoral contexts.

Supporting H1 (Model 1), sentiment scores demonstrated a significant negative relationship with engagement (β = -0.212, $p < 0.001$), supporting H1. Both non-campaign (β = 0.375, $p < 0.001$) and local election periods (β = 0.661, p ¡ 0.001) showed stronger engagement effects compared to general elections. Model 2 further confirms this relationship with significant negative interactions between sentiment and engagement during non-campaign (β = -0.254, $p < 0.001$) and local election periods (β = -0.232, $p < 0.050$).

Supporting H2, engagement score positively affects voting intention (β = 0.005, $p < 0.001$) (Model 3). Local elections exhibited a higher mean voting intention (M = 0.277) compared to non-campaign periods (M = 0.211) and general elections (M = 0.136). Model 4 provides additional evidence for H2, showing engagement scores have a significant positive relationship with voting intention (β = 0.006, $p < 0.001$), indicating higher engagement translates to increased voting likelihood. When compared to general election periods, both non-campaign (β = 0.003, $p < 0.05$) and local election periods (β = 0.007, $p < 0.01$) showed positive main effects. The interaction between engagement and non-campaign periods approaches significance (β = -0.002, $p = 0.067$), while local election interactions remain non-significant.

Model 5 demonstrates that sentiment score negatively relates to voting intention (β = -0.002, $p < .001$), supporting H3. Model 6 reveals this relationship is driven by periods outside of the general election campaign, with significant negative sentiment effects during non-campaign (β = -0.005, $p < .05$) and local election periods (β = -0.010, $p < 0.001$).

Causal mediation analysis (Model 7) revealed that engagement partially mediated the effect of sentiment on voting intention. The Average Causal Mediation Effect (ACME) was significant (-0.001, $p < 0.001$), with a direct effect (ADE) of -0.002 ($p < .05$) and a total effect of -0.002

($p < 0.001$). 38.4% of the effect of sentiment on voting intention was mediated by engagement.

A multi-group structural equation model (SEM) confirmed that sentiment exerts a negative effect on engagement across all three electoral periods (β = -0.283), while engagement positively predicts voting intention (β = 0.002). However, the indirect (mediated) effect of sentiment on voting intention through engagement was small and statistically non-significant across all groups. These findings suggest that although engagement serves as a mediator in the relationship between sentiment and voting intention, the strength of this mediated pathway is limited.

Table 1: Linear Regression Results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	43.57^{***}	43.49^{***}	-8.04^{***}	-7.96^{***}	-7.85^{***}	-7.84^{***}
	(4.43)	(4.42)	(0.11)	(0.12)	(0.11)	(0.11)
sentiment_score	-0.21^{***}	0.00			-0.00^{***}	0.00
	(0.03)	(0.07)			(0.00)	(0.00)
dummy_factorNoCampaign	0.37^{***}	0.37^{***}	0.00	0.00^{*}	0.00^{**}	0.00^{**}
	(0.05)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
dummy_factorLocalElection	0.66^{***}	0.66^{***}	0.01^{*}	0.01^{**}	0.01^{***}	0.01^{***}
	(0.09)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)
views_log	0.67^{***}	0.67^{***}	-0.00^{***}	-0.00^{***}	0.00^{***}	0.00^{***}
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
date	-0.00^{***}	-0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
sentiment_score:dummy_factorNoCampaign		-0.25^{***}				-0.00^{*}
		(0.07)				(0.00)
sentiment_score:dummy_factorLocalElection		-0.23^{*}				-0.01^{***}
		(0.10)				(0.00)
engagement_score			0.00^{***}	0.01^{***}		
			(0.00)	(0.00)		
engagement_score:dummy_factorNoCampaign				-0.00		
				(0.00)		
engagement_score:dummy_factorLocalElection				0.00		
				(0.00)		
R^2	0.65	0.65	0.93	0.93	0.92	0.93
Adj. R^2	0.65	0.65	0.93	0.93	0.92	0.93
Num. obs.	1388	1388	1388	1388	1388	1388

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

5 Discussion

Having established the statistical relationships between negative sentiment, engagement, and voting intentions across different electoral contexts, we now turn to interpreting these findings within the broader theoretical framework of political communication and social media influence.

Our analysis confirms our first hypothesis and shows us that sentiment scores have a significant negative relationship with engagement (β = -0.212, $p < 0.001$), indicating tweets with more negative sentiment generated higher engagement. This aligns with existing literature that emphasizes emotion as a powerful driver of political communication. As noted by Antypas, Preece, Camacho-Collados (2023) and Pivecka, Ratzinger, Florack (2022), tweets that elicit high emotional arousal, particularly negative emotions like anger, anxiety, and moral outrage, receive significantly more engagement. Our findings corroborate Tsugawa and Ohsaki's (2013) research showing that negative tweets diffuse wider and faster than positive or neutral tweets by at least 20%, and Steiglitz and Dang-Xuan's (2013) evidence that sentiment and retweet quantity are stronger for negatively-charged tweets.

Our models support the second hypothesis by demonstrating that engagement score has a significant positive effect on voting intention (β = 0.005, $p < 0.001$). This relationship remained robust even when controlling for electoral context, with engagement scores maintaining a significant positive relationship with voting intention (β = 0.006, $p < 0.001$), indicating higher engagement translates to increased voting likelihood. This finding supports the growing evidence that digital engagement can influence voter behaviour. As Bär, Pröllochs, & Feuerriegel (2025) found, social media visibility significantly boosts vote share over abstention. Our results align with Gordon and Hartmann's (2013) demonstration that political advertising has robust positive effects on electoral outcomes. The mechanism may be similar to what Conover et al. (2012) observed, where cohesive online networks enable faster information diffusion and wider message amplification.

We also showed that sentiment has a significant negative relationship with voting intention (β = -0.002, $p < 0.001$), suggesting that more negative sentiment in communications corresponds with higher voting intention, corroborating our third hypothesis. This aligns with Conover and Feldman's (1986) argument that emotion plays a primary role in shaping political judgments, and Boukes' (2022) finding that emotionally framed political messages boost credibility and engagement. The effectiveness of negative sentiment may be explained by Gil de Zúñiga et al.'s (2020) observation that viral populist messaging typically relies on emotional resonance rather than factual accuracy.

Our mediation analysis reveals that engagement significantly mediates the relationship between sentiment and voting intention. This partial mediation suggests a complex mechanism similar to what was observed in Trump's 2016 campaign, which combined traditional media performances with highly effective digital engagement (Bucy et al., 2020; Benkler et al., 2017). The effectiveness of this strategy may be amplified by platform algorithms that disproportionately promote divisive content (Huszár et al., 2023), making emotional language a core tactical element in digital political strategy. These findings have significant implications for understanding political communication in the digital age, particularly for populist actors like Reform UK who are gaining electoral traction through emotional appeals and anti-establishment narratives.

6 Conclusion

Our findings indicate a statistically significant negative relationship between sentiment and engagement, which in turn positively influences voting intention. Mediation analysis reveals engagement partially mediates the relationship between sentiment and voting intention, accounting for 38.4% of the total effect. Despite this indirect pathway, sentiment maintains a direct negative relationship with voting intention, suggesting that while negative sentiment drives engagement, it also independently increases voting likelihood across all election periods.

This study makes a significant contribution to literature on digital political communication by providing one of the first empirical analyses of Reform UK's social media strategy. By quantifying the relationship between negative sentiment, engagement, and voting intentions, we bridge an important gap in understanding how emerging populist parties leverage emotional appeals in the digital sphere. This work extends existing frameworks by providing a robust statistical model that quantifies the mediating role of engagement between sentiment and electoral outcomes, advancing our understanding beyond correlational observations to a more nuanced causal pathway.

As citizens encounter political content online, our research illuminates the subtle ways emotional appeals may influence political behavior, potentially enhancing media literacy and critical engagement with political messaging. In an era where platform algorithms continue to evolve and political communication adapts accordingly, this research provides a crucial foundation for understanding the complex interplay between sentiment, engagement, and democratic participation in an increasingly digital political landscape.

Some limitations affect our study. First, our dataset contains significantly more data for non-campaign than campaign periods, potentially skewing period comparisons. Second, our sentiment analysis relied on a predefined package rather than machine learning, limiting accuracy in capturing political nuance. Third, manual data collection without API access introduced room for human error and restricted our analysis to a single election cycle. Fourth, due to time constraints we were unable to compare Reform UK's sentiment-engagement-voting intention relationship with other UK parties (Conservative/Labour) or similar populist parties. Finally, while we controlled for major factors like time, period, and algorithm effects, we acknowledge that unaccounted variables may influence the observed relationships.Future research should address these limitations through more balanced datasets, advanced sentiment analysis techniques, and comparative studies across multiple parties and election cycles.

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A Appendix

A.1 Data Cleaning

Before conducting the primary analyses, we screened the data for missing values. Of the 1490 tweets compiled, 14 entries were excluded due to the absence of corresponding polling data as expected given tweet collection exceeded 5 days beyond the last polling update. An additional 88 tweets were removed after filtering out tweets with erroneous engagement metrics, specifically where the number of likes exceeded the number of views. No additional missing values or duplicate tweets were identified in the dataset. This cleaning process resulted in a final sample of 1388 tweets.

A.2 Explanation of Models

All models included control variables for views and date as well as a categorical dummy variable representing the election period (p1, p2, p3). The models were structured as follows:

$$E \sim \text{Sentiment} + \text{Dummy} + \ln(\text{Views}) + \text{Date} \tag{1}$$
$$E \sim \text{Sentiment} \times \text{Dummy} + \ln(\text{Views}) + \text{Date} \tag{2}$$
$$\text{Voting intention} \sim E + \text{Dummy} + \ln(\text{Views}) + \text{Date} \tag{3}$$
$$\text{Voting intention} \sim E \times \text{Dummy} + \ln(\text{Views}) + \text{Date} \tag{4}$$
$$\text{Voting intention} \sim \text{Sentiment} + \text{Dummy} + \ln(\text{Views}) + \text{Date} \tag{5}$$
$$\text{Voting intention} \sim \text{Sentiment} \times \text{Dummy} + \ln(\text{Views}) + \text{Date} \tag{6}$$

All regressions were performed in RStudio (version 4.3.2) using lm() function to assess the direct effects of sentiment, engagement and voting intention and how these relationships may vary across the different election periods.

A.3 Mediation Analysis (Causal Mediation)

To preliminarily test H4 - that the relationship between sentiment and voting intention is mediated by engagement - we conducted a causal mediation analysis using linear regression. The linear model where voting intention was regressed on engagement score, sentiment score, controls, and a dummy variable (political periods).

$$\text{Voting intention} \sim E + \text{Sentiment} + \ln(\text{Views}) + \text{Date} + \text{Dummy} \tag{7}$$

This allowed us to estimate both the direct and indirect effects of sentiment on voting intention via engagement. The analysis was conducted using the mediation() package in R. Next, we conducted nonparametric bootstrapping with 1000 simulations to calculate the ACME, ADE and the total effect (see table 9).

A.4 Multi-level Structural Equation Modelling

Methodology rationale: To examine H4 - whether the relationship between sentiment and voting intention via engagement - varied across political periods and better account for measurement error in the latent variable of engagement, we conducted a multi-group Structural Equation Model (SEM). This approach allowed us to retain engagement as a latent variable (measured by likes, replies, retweets) and simultaneously estimate the indirect and direct effects across the

General Election (n = 287), No Campaign (n = 904), and Local Election (n = 197).

The model was estimated using maximum likelihood (ML) estimation using the lavaan() package (R version 4.3.2). A full mediation model, where sentiment affects voting intention only indirectly via engagement, was compared against a partial mediation model which allows for both direct and indirect effects. The partial mediation model was preferred as it better demonstrated the presence of a direct effect from sentiment to voting intention, even when accounting for the mediating role of engagement.

To assess whether this mediation varied across the different election periods, we compared an unconstrained model allowing all parameters to vary for each group, and a constrained model imposing equality constraints for each group. The chi-square difference test indicated that the unconstrained model provided a significantly better fit than the constrained model. χ^2 (8) = 672.74, $p < .001$, suggesting relationships differed across political periods. Overall, model fit indices supported this model (CFI = 0.996, TLI = 0.993, SRMR = 0.039), though RMSEA was high (0.209), suggesting some model misspecification.

Table 2: Model 1: Linear Regression Results

Variable	**Estimate**	**Std. Error**	**t value**	**p-value**
(Intercept)	43.570	4.432	9.829	$<$ 2e-16***
sentiment_score	-0.212	0.026	-8.082	1.38e-15***
dummy_factorNoCampaign	0.375	0.055	6.819	1.37e-11***
dummy_factorLocalElection	0.661	0.090	7.318	4.25e-13***
views_log	0.666	0.014	46.926	$<$ 2e-16***
date	-2.956e-08	2.566e-09	-11.521	$<$ 2e-16***

Model Statistics	
Residual standard error	0.570 on 1382 degrees of freedom
Multiple R-squared	0.650
Adjusted R-squared	0.649
F-statistic	513.7 on 5 and 1382 DF
p-value	$<$ 2.2e-16

Residual Summary	
Min	-2.093
1Q	-0.348
Median	0.080
3Q	0.418
Max	1.382

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 3: Model 2: Linear Regression Results with Interaction Terms

Variable	**Estimate**	**Std. Error**	**t value**	**p-value**
(Intercept)	43.490	4.419	9.842	< 2e-16***
sentiment_score	0.001	0.067	0.012	0.990
dummy_factorNoCampaign	0.365	0.055	6.662	3.89e-11***
dummy_factorLocalElection	0.657	0.090	7.290	5.22e-13***
views_log	0.666	0.014	47.098	< 2e-16***
date	-2.952e-08	2.558e-09	-11.539	< 2e-16***
sentiment_score:dummy_factorNoCampaign	-0.254	0.074	-3.431	0.001***
sentiment_score:dummy_factorLocalElection	-0.232	0.097	-2.395	0.017*

Model Statistics	
Residual standard error	0.568 on 1380 degrees of freedom
Multiple R-squared	0.653
Adjusted R-squared	0.651
F-statistic	371.2 on 7 and 1380 DF
p-value	< 2.2e-16

Residual Summary	
Min	-2.090
1Q	-0.350
Median	0.077
3Q	0.422
Max	1.374

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4: Model 3: Linear Regression Results

Variable	**Estimate**	**Std. Error**	**t value**	**p-value**
(Intercept)	-8.045	0.114	-70.647	< 2e-16***
engagement_score	0.005	0.001	7.278	5.65e-13***
dummy_factorNoCampaign	0.003	0.001	1.926	0.054.
dummy_factorLocalElection	0.005	0.002	2.372	0.018*
views_log	-0.002	0.001	-3.464	0.001***
date	4.774e-09	6.670e-11	71.567	< 2e-16***

Model Statistics	
Residual standard error	0.014 on 1382 degrees of freedom
Multiple R-squared	0.927
Adjusted R-squared	0.926
F-statistic	3490 on 5 and 1382 DF
p-value	< 2.2e-16

Residual Summary	
Min	-0.034
1Q	-0.010
Median	-0.002
3Q	0.012
Max	0.034

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 5: Model 4: Linear Regression Results with Interaction Terms

Variable	Estimate	Std. Error	t value	p-value
(Intercept)	-7.957	0.118	-67.442	< 2e-16***
engagement_score	0.006	0.001	5.831	6.87e-09***
dummy_factorNoCampaign	0.003	0.001	2.458	0.014*
dummy_factorLocalElection	0.007	0.002	3.029	0.002**
views_log	-0.002	0.001	-3.677	0.000***
date	4.724e-09	6.897e-11	68.487	< 2e-16***
engagement_score:dummy_factorNoCampaign	-0.002	0.001	-1.835	0.067.
engagement_score:dummy_factorLocalElection	0.002	0.001	1.346	0.178

Model Statistics	
Residual standard error	0.014 on 1380 degrees of freedom
Multiple R-squared	0.927
Adjusted R-squared	0.927
F-statistic	2507 on 7 and 1380 DF
p-value	< 2.2e-16

Residual Summary	
Min	-0.033
1Q	-0.010
Median	-0.002
3Q	0.012
Max	0.035

Signif. codes: 0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1

Table 6: Model 5: Linear Regression Results

Variable	Estimate	Std. Error	t value	p-value
(Intercept)	-7.849	0.112	-70.321	< 2e-16***
sentiment_score	-0.002	0.001	-3.753	0.000***
dummy_factorNoCampaign	0.004	0.001	3.039	0.002**
dummy_factorLocalElection	0.008	0.002	3.709	0.000***
views_log	0.001	0.000	3.641	0.000***
date	4.640e-09	6.461e-11	71.807	< 2e-16***

Model Statistics	
Residual standard error	0.014 on 1382 degrees of freedom
Multiple R-squared	0.925
Adjusted R-squared	0.924
F-statistic	3387 on 5 and 1382 DF
p-value	< 2.2e-16

Residual Summary	
Min	-0.030
1Q	-0.011
Median	-0.003
3Q	0.013
Max	0.031

Signif. codes: 0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1

Table 7: Model 6: Linear Regression Results with Interaction Terms

Variable	**Estimate**	**Std. Error**	**t value**	**p-value**
(Intercept)	-7.841	0.111	-70.586	< 2e-16***
sentiment_score	0.002	0.002	1.310	0.190
dummy_factorNoCampaign	0.004	0.001	3.045	0.002**
dummy_factorLocalElection	0.009	0.002	3.798	0.000***
views_log	0.001	0.000	3.721	0.000***
date	4.635e-09	6.431e-11	72.075	< 2e-16***
sentiment_score:dummy_factorNoCampaign	-0.005	0.002	-2.512	0.012*
sentiment_score:dummy_factorLocalElection	-0.010	0.002	-4.040	5.65e-05***

Model Statistics	
Residual standard error	0.014 on 1380 degrees of freedom
Multiple R-squared	0.925
Adjusted R-squared	0.925
F-statistic	2447 on 7 and 1380 DF
p-value	< 2.2e-16

Residual Summary	
Min	-0.030
1Q	-0.010
Median	-0.002
3Q	0.013
Max	0.031

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 8: Model 7: Linear Regression Results

Variable	**Estimate**	**Std. Error**	**t value**	**p-value**
(Intercept)	-8.042	0.112	-71.536	< 2e-16***
engagement_score	0.004	0.001	6.629	4.84e-11***
sentiment_score	-0.002	0.001	-2.302	0.021*
views_log	-0.002	0.001	-2.896	0.004**
date	4.769e-09	6.639e-11	71.832	< 2e-16***
dummy	0.003	0.001	2.410	0.016*

Model Statistics	
Residual standard error	0.014 on 1382 degrees of freedom
Multiple R-squared	0.927
Adjusted R-squared	0.927
F-statistic	3504 on 5 and 1382 DF
p-value	< 2.2e-16

Residual Summary	
Min	-0.035
1Q	-0.010
Median	-0.002
3Q	0.012
Max	0.034

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 9: Causal Mediation Analysis Results (Bootstrapping)

Effect	**Estimate**	**CI Lower**	**CI Upper**	**p-value**
ACME	-0.001	-0.001	0.00	<2e-16***
ADE	-0.002	-0.003	0.00	0.02*
Total Effect	-0.002	-0.004	0.00	<2e-16***
Prop. Mediated	0.384	0.217	0.81	<2e-16***

Analysis Details

Method	Nonparametric Bootstrap with Percentile Method
Sample Size Used	1388
Simulations	1000

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 10: Chi-Squared Difference Test Results

Model	**Df**	**AIC**	**BIC**	**Chisq**	**Chisq diff**	**RMSEA**	**Df diff**	**p-value**
fit	30	-3637.7	-3386.4	638.05	-	-	-	
fit_constrained	38	-3229.5	-3020.1	1310.79	672.74	0.424	8	< 2.2e-16***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 11: Structural Equation Model Results - Model Fit Statistics

Fit Measure	**Value**
Test statistic	638.048
Degrees of freedom	30
P-value (Chi-square)	0.000
Comparative Fit Index (CFI)	0.996
Tucker-Lewis Index (TLI)	0.993
RMSEA	0.209
RMSEA 90% CI Lower	0.195
RMSEA 90% CI Upper	0.224
SRMR	0.039
AIC	-3637.734
BIC	-3386.425

Table 12: SEM Parameter Estimates by Group - Standardized Effects

Path	**GeneralElection**	**NoCampaign**	**LocalElection**
Sentiment → Engagement (a)			
Standardized	-0.078	-0.118	-0.120
Engagement → Voting Intention (b)			
Standardized	0.135	0.063	0.105
Sentiment → Voting Intention (c')			
Standardized	-0.043	-0.030	-0.051
Indirect Effect (a×b)			
Standardized	-0.011	-0.007	-0.013
Total Effect			
Standardized	-0.054	-0.037	-0.064

Model Details	
Estimator	ML
Optimization method	NLMINB
Model parameters	54
Equality constraints	6
Iterations	1257
Sample sizes by group:	
GeneralElection	287
NoCampaign	904
LocalElection	197

Table 13: Descriptive Statistics by Election Type

Election Type	**Sentiment Score Mean (SD)**	**Engagement Score Mean (SD)**	**Voting Intention Mean (SD)**
GeneralElection	-0.017 (0.499)	0.072 (1.090)	0.136 (0.021)
NoCampaign	-0.120 (0.611)	-0.005 (0.942)	0.211 (0.036)
LocalElection	0.022 (0.582)	-0.080 (0.834)	0.277 (0.020)

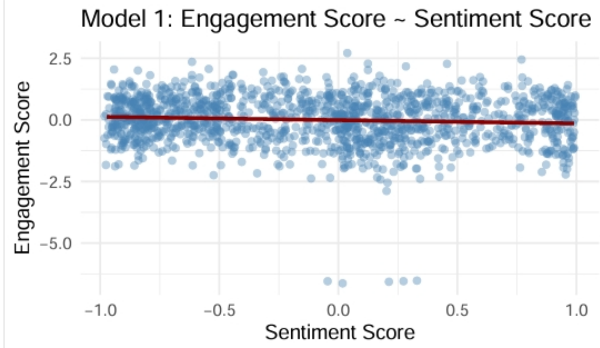


Figure 1:

Figure 2:

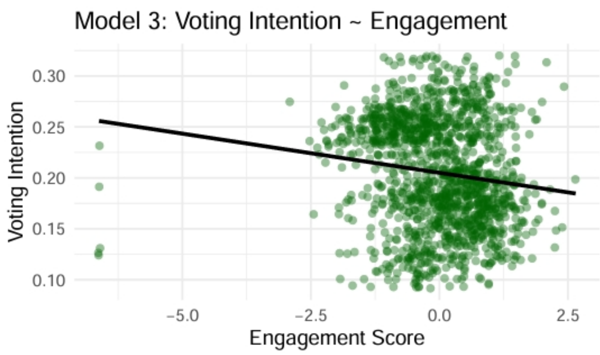
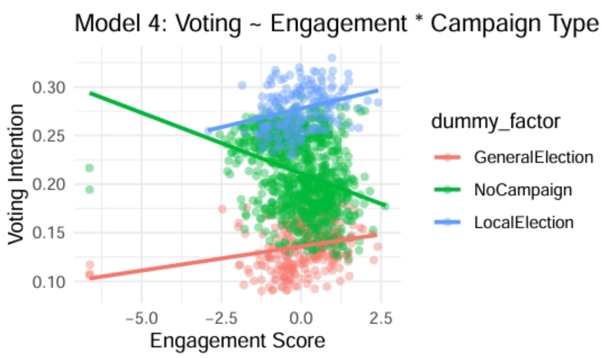


Figure 3:



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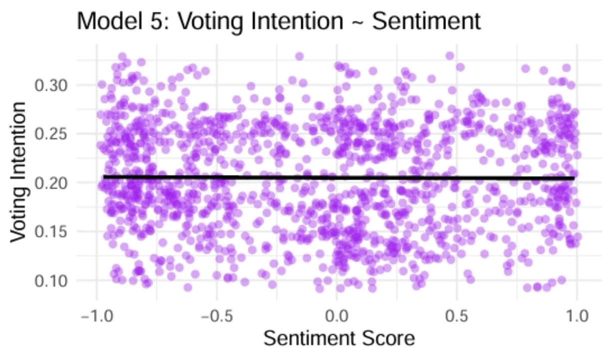

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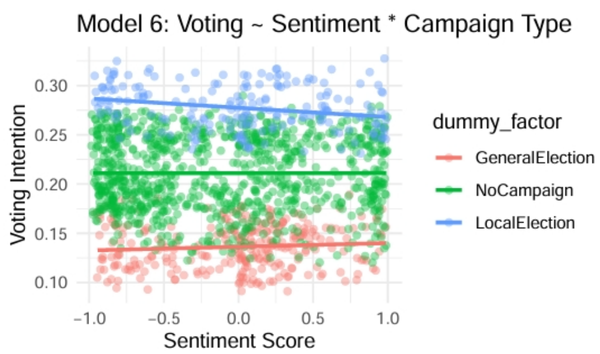

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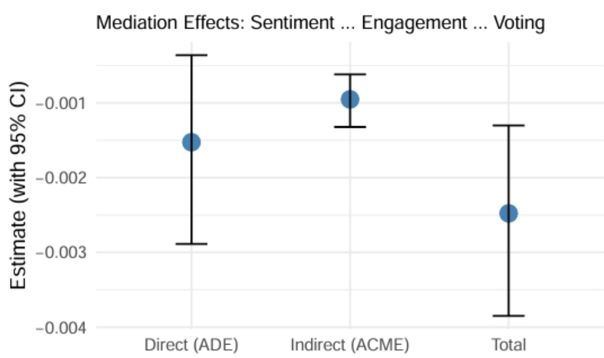

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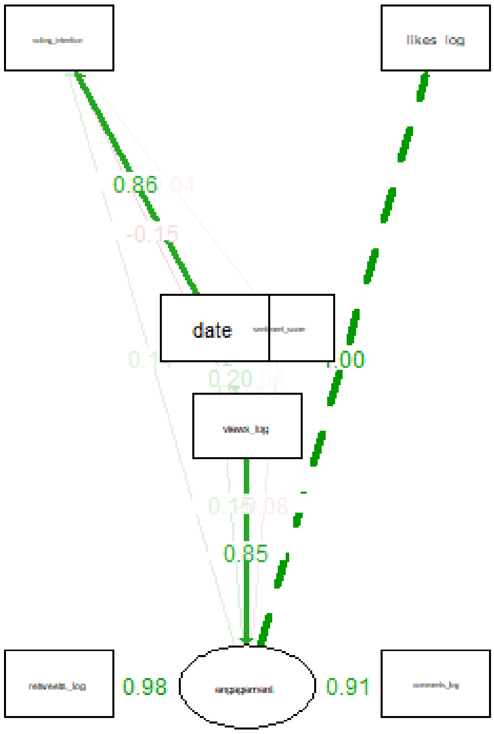

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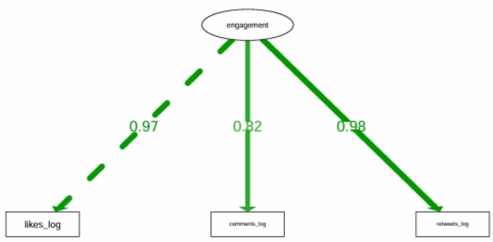

Figure 9:

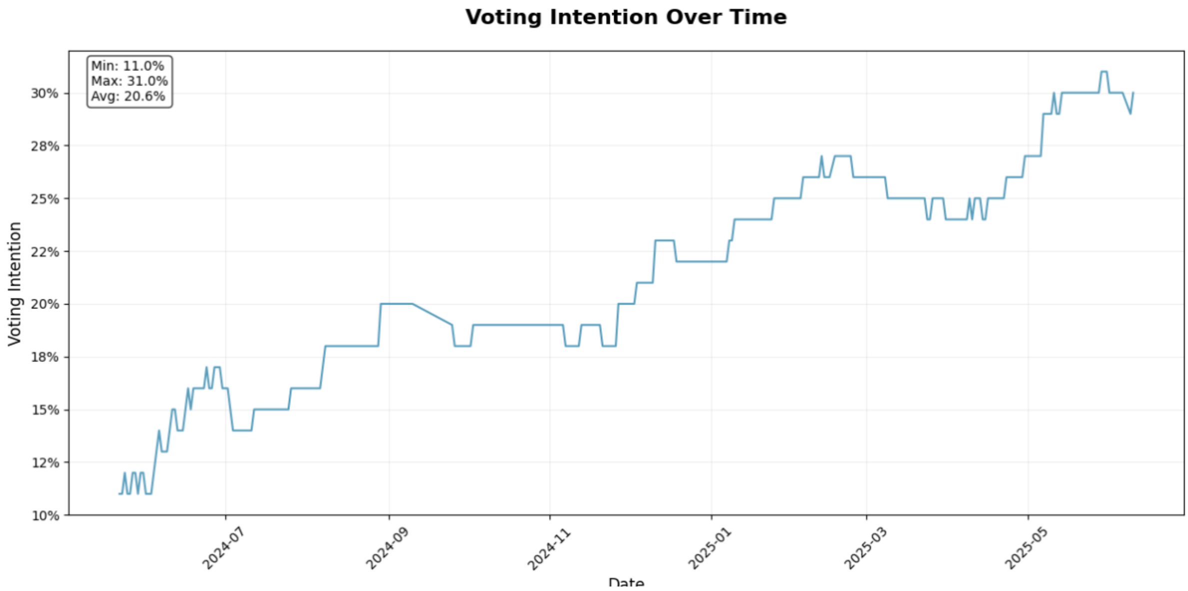

Figure 10: Data from Politico UK Polls of Polls (2025)