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Judicial rulings and political narratives: Analyzing the impact of Roe v. Wade's overturning on digital discourse using machine learning

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Nikolina Klatt

Judicial Rulings and Political Narratives

Analyzing the Impact of Roe v. Wade's Overturning
on Digital Discourse Using Machine Learning

Discussion Paper

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Abstract

Judicial Rulings and Political Narratives

Analyzing the Impact of Roe v. Wade's Overturning on Digital Discourse
Using Machine Learning

by Nikolina Klatt

How do judicial decisions influence political discourse, particularly in areas as contentious as abortion rights? This study investigates how the overturning of Roe v. Wade affected the narrative strategies of U.S. representatives on social media, focusing on variations by party affiliation and geography. While there is literature on the influence of judicial decisions on public opinion and policy, the effect on political narratives remains underexplored. To address this gap, the study analyzes 5,293 tweets from U.S. representatives in 2022 by supervised text classification and statistical modeling to identify shifts in narrative strategies. The study found the leaked opinion draft acted as a catalyst, which prompted an increase in stories of decline—narratives that emphasize a worsening situation—particularly for Republicans. This study provides empirical evidence of how political narratives evolve in response to landmark judicial changes and insights into the strategic use of narratives by political actors in digital communication.

1. Introduction

This study is motivated by the need to understand how narratives are strategically employed by political actors, particularly in the context of significant judicial decisions that reshape the legal and moral landscape. The overturning of *Roe v. Wade* represents a crucial moment in U.S. political and social history, which fundamentally altered reproductive rights and triggered a wide-reaching nationwide debate (Harvard Kennedy School 2022). This decision not only impacts the legal status of abortion but also catalyzes significant shifts in public opinion, political mobilization, and legislative action across states. As a landmark ruling that reverses nearly five decades of established constitutional precedent, it starkly highlights the power of the judiciary to influence societal norms and values. In 2022, the political discourse surrounding abortion was influenced by several critical events that framed the narrative beyond the overturning of *Roe v. Wade*. The leaked opinion draft earlier in the year provided an unprecedented preview of the impending decision, which sparked an immediate and widespread public and political reaction (Gerstein and Ward 2022; Politico 2022). The proposal of a 15-week abortion ban bill further polarized opinions and highlighted the legislative push to redefine abortion rights at the federal level (Karni 2022). Additionally, the midterm elections later in the year became a pivotal battleground, with abortion rights as a central issue (Kann et al. 2024; Kurtzleben 2022). These events collectively contributed to an intensely charged political environment, making 2022 a landmark year for abortion discourse in the United States. This makes it a crucial subject for examining the relationship between judicial action and narrative strategies, as it provides a clear instance of how legal decisions can reshape political discourse.

This article answers the central question: What is the effect of the overturning of *Roe v. Wade* on US representatives' narratives of abortion? Given the profound influence of judicial decisions on political narratives, the study investigates how the overturning of *Roe v. Wade* has impacted the narrative strategies employed by US representatives in their public discourse about abortion on social media. This research specifically examines whether and how the narrative strategies have shifted in terms of stories of decline (narratives that emphasize a worsening situation) and stories of rising (narratives that emphasize improvement) (Stone 2012), and whether these shifts vary by party affiliation, geographic location based on state-level abortion laws, and the immediacy of the leaked draft versus the actual judicial decision.

The literature on political communication is crucial for understanding the dynamics of public opinion, policy-making, and electoral strategies. Within this field, narratives—defined broadly as stories used to make sense of events and actions—are recognized as fundamental tools through which political realities are constructed and conveyed. Roe (1994) and Stone (2012) have highlighted the

importance of narratives in simplifying complex policy issues and influencing public opinion.

The study utilizes a comprehensive dataset of tweets from U.S. representatives in 2022. The dataset includes 5,293 tweets that specifically mention abortion, collected by using the Twitter API and filtered to remove retweets and duplicates. This dataset provides a rich source of real-time political communication, which allows for an in-depth analysis of narrative shifts before and after the overturning of *Roe v. Wade*.

The analysis employs supervised text classification by using Support Vector Machines (SVM) with a polynomial kernel to classify tweets into stories of decline or stories of rising. This is followed by a series of generalized linear mixed models (GLMM) and a generalized additive model (GAM) to examine the temporal dynamics and interaction effects of party affiliation and state-level abortion laws on narrative strategies.

The empirical analyses reveal a significant shift in the narrative strategies of U.S. representatives on Twitter in response to the overturning of *Roe v. Wade*. This shift is particularly pronounced among Republican representatives, who strategically use decline narratives even when a celebratory framing might be expected. The analysis also highlights the geographic variability in narrative strategies, with representatives from states with trigger laws exhibiting distinct narrative patterns. Narrative strategies are strategically used to manage public perception and voter behavior, which align with broader, more moderate constituent bases and highlight the dynamic interplay between judicial decisions and political communication.

As such, my paper makes two contributions: First, it advances the fields of political science and political communication by innovatively analyzing political narratives surrounding the highly contentious issue of abortion in the United States. Second, the study provides empirical evidence of how political narratives evolve in response to landmark legal changes.

The article is structured as follows: After the introduction, a detailed literature review is presented, followed by the theoretical framework and research question. Next, the data and methodology are described, including the supervised text classification and statistical models used. The results section presents the empirical findings, and the discussion interprets these findings in the context of the existing literature. Finally, the paper concludes with a summary of the contributions, limitations, and suggestions for future research.

2. Literature Review

2.1. Narratives in Political Science

Narratives are essential tools for understanding how individuals and groups make sense of their realities. As such, they also play an important role within political science. Patterson and Monroe (1998) argue that narratives, or stories, play a crucial role in organizing cognitive processes and shaping cultural perceptions, thereby

influencing political behavior. Roe (1994) applied narrative policy analysis from literary theory to public policy issues, which emphasizes how stories help us understand and manage complex policy challenges.

Moreover, in the seminal work *Policy Paradox*, Deborah Stone (2012) argues that narratives are essential tools used by political actors to frame issues, define problems, and influence public opinion as well as policymaking processes. Thus, narratives help simplify complex policy issues into stories that are easier for the public and policymakers to understand and relate to. Through these narratives, political actors can emphasize certain aspects of an issue while minimizing others. This strategy effectively shapes the policy agenda and influences how policy problems are perceived. Furthermore, Stone emphasizes the strategic use of stories in the political arena to evoke emotions, create identities, and mobilize support. She illustrates how narratives can construct realities that become powerful influences on policy decisions because they resonate with people's values, fears, and aspirations.

2.2. Political Communication on Social Media

Social media is utilized in various ways, such as mobilization and campaigning (Tufekci and Wilson 2012), political polarization (Pariser 2011), surveillance and transparency (Margetts 2019), and combating disinformation and manipulation (Allcott and Gentzkow 2017). Furthermore, it plays a role in how politicians, parties, and citizens engage and influence public opinion. It allows politicians and public officials to communicate directly with the electorate and bypass traditional media gatekeepers (Enli and Skogerbø 2013). Social media influences public opinion by providing a space for public discourse on political issues. It amplifies certain viewpoints through algorithms that curate content based on user preferences, potentially shaping political attitudes and beliefs (Neubaum and Krämer 2017). Thus, Twitter¹, as a prominent example, serves as a unique platform for political narratives.

2.3. Abortion in Political Discourse

The discourse surrounding abortion in the United States is a paradigm of the deep polarization that characterizes contemporary political debates, which is also carried out on social media. This issue not only illustrates the broader societal divisions but also the intensity with which ideological battles are fought. The polarization over abortion is manifested through the language employed, the narratives crafted, and the strategic approaches adopted by various political and ideological groups.

¹ In July 2023, Twitter was renamed to X. Since all data was scrapped in January 2023 when the platform was still called Twitter, the study refers to Twitter instead of X.

The discourse has significantly contributed to the partisan polarization observed within the American political landscape. There is a stark dichotomy between the “pro-life” framing predominantly adopted by Republican parties and candidates and the “pro-choice” framing by their Democratic counterparts (Adams 1997; Carmines and Woods 2002; Carsey and Layman 2006; Killian and Wilcox 2008). This polarization is not merely a reflection of differing policy preferences but signifies deeper ideological divisions that influence a wide array of political behaviors and alignments. The binary framing of abortion—centered around moral, ethical, rights-based, health, and religious arguments—serves to solidify partisan identities.

The abortion discourse is heavily influenced by moral and ethical considerations (Luker 2009). “Pro-life” advocates frame abortion as a moral issue concerning the sanctity of life and the rights of the unborn, whereas “pro-choice” supporters emphasize women's autonomy over their bodies. The debate is also framed in terms of rights: the right to life versus the right to choose (Siegel 2008). “Pro-choice” advocates highlight the importance of reproductive rights as part of women's rights and health care, while “pro-life” supporters focus on the fetus' right to life. Both sides use health and safety in their framing of the issue (Biggs et al. 2017). “Pro-choice” advocates argue that access to safe and legal abortion services is essential for women's health and safety. In contrast, “pro-life” groups often claim that abortion poses risks to women's physical and mental health. Religious beliefs significantly influence the abortion debate, with many “pro-life” advocates who draw on religious doctrines to oppose abortion (Cook, Jelen, and Wilcox 1992). Conversely, “pro-choice” discourse often adopts a secular framing, which emphasizes individual choice and separation of church and state.

For the most part, legislative initiatives have promised to either protect abortion rights or introduce restrictions (Medoff 2010). Furthermore, politicians and parties use abortion to mobilize specific voter segments (Adams 1997; Cook, Jelen, and Wilcox 1994). This aligns well with the fact that abortion as an electoral issue has a significant impact on women's voting behavior. In fact, for many women a candidate's stance on abortion is a key factor in their electoral choices (Abramowitz 1995; Sanbonmatsu 2002). The use of specific language and symbolic devices in political rhetoric around abortion further frames the issue in ways that resonate with voters' values and beliefs (Luker 2009).

2.4. Impact of Judicial Decisions on Political Narratives

Judicial decisions profoundly impact political narratives in several ways. These decisions can redefine the legal and moral landscapes, mobilize or demobilize political actors and constituents, shift the focus and strategies of political campaigns, and lead to new policy debates.

The discourse around abortion rights has been significantly shaped by the legal status of abortion, which influences how these themes are discussed in political

narratives (Ziegler 2020). Landmark judicial decisions often serve as a rallying point for political actors, mobilizing activists, voters, and policymakers (Staggenborg 1988). The ruling of *Roe v. Wade* in 1973, for instance, mobilized both “pro-choice” and “pro-life” activists, each framing the decision in ways that align with their broader narratives and goals (Rohlinger 2006). Thus, judicial decisions can shift the thematic focus of political campaigns (Devins and Baum 2019). Candidates and parties often adjust their messaging to emphasize their stance on the issue at hand, using the decision as evidence of the need for electoral support to either uphold or challenge the new legal status quo. They can lead to new policy debates and legislative efforts either to align with or resist the court's ruling. The overturning of *Roe v. Wade*, for example, has had implications for state-level abortion laws and the strategies political actors use to either restrict or protect abortion access. Furthermore, Supreme Court rulings also influence voting patterns on abortion (Roh and Haider-Markel 2003). They tend to mobilize “pro-choice” voters, leading to an increase in “pro-choice” voting in elections following such decisions. This emphasizes the significant role of Supreme Court rulings in influencing public opinion and policy-making activity concerning abortion.

Overall, judicial decisions not only impact the legal status of contentious issues but also play a significant role in shaping the political narratives surrounding those issues. These narratives, in turn, influence public opinion, political mobilization, campaign strategies, media coverage, and future policy and legislative efforts. While there is literature on the influence of judicial decisions on public opinion and policy and on narratives used within legal texts and judicial opinions (Hanne and Weisberg 2018; Stern 2018), the effect of judicial decisions on political narratives remains underexplored. This gap highlights the innovative potential of my research, which applies the political communication theory and narrative policy analysis to understand how a significant judicial decision, like the overturning of *Roe v. Wade*, influences the narrative strategies employed by political actors in their public communications.

3. Theoretical Framework and Research Question

3.1. Political Communication and Framing Theory

The foundation for the theoretical considerations of this analysis is set by political communication theory, which examines how information is used in political processes, including the role of media, propaganda, and strategic communication (Chong and Druckman 2007). It provides insights into how political narratives around issues like abortion are crafted, disseminated, and received by the public. Framing theory is an integral part of political communication theory. Originating in the work of Erving Goffman (1974), it explores how information is presented by media, politicians, and other actors to influence public perception and interpretation of issues, events, or policies. In the context of politics, framing is used to analyze how

political issues are constructed and communicated to the public, highlighting certain aspects while omitting or downplaying others (Entman 1993). The manipulation of emphasis can significantly affect public opinion, policy preferences, and political behavior. For instance, the framing of a policy issue as a crisis may generate urgency and support for specific political actions, while framing it as a matter of personal freedom might evoke resistance to government intervention. Regarding abortion, framing might focus on human rights, public health, morality, or legality, with each shaping the discourse in distinct ways.

3.2. Narrative Stories

Stone (2012) outlines two major themes of story types—*stories of power* and *stories of change*—that policy actors use to frame issues and persuade their audience. The story types help to structure and communicate political narratives by emphasizing different aspects of an issue depending on the policy actor's agenda. *Stories of change* (2012, 159–68) concentrate on the progression or deterioration over time within a policy issue or social condition. These narratives can be optimistic (*stories of rising*), or pessimistic (*stories of decline*). More specifically, stories of decline focus on the worsening of a situation or problem over time. In the context of abortion law, a story of decline might emphasize the increasing restrictions on women's reproductive rights². In contrast, stories of rising are defined as narratives that chart progress or improvement from a less favorable past to a better present or future. The narrative emphasizes transformation and advancement, suggesting that deliberate efforts or positive changes have led to a current state that is superior to what preceded it. In abortion policy, a story of rising could focus on the narrative of increasing access to reproductive healthcare over time³. Policy actors strategically use story types in their narratives to shape public opinion, gather support, and advance their political agendas.

3.3. Research Question and Hypotheses

Bringing these theoretical aspects together and focusing on a timely political subject, this study asks the following central research question: **What is the effect of the overturning of Roe v Wade on US representatives' narratives of abortion?** To answer this question, I investigate the impact of the overturning of Roe v. Wade on the narrative strategies used by US representatives in their public discourse

² Example for story of decline: "Should this decision become law, roughly half the states in our country will make all or nearly all abortions illegal, leading to gross inequalities in health care access." Christopher A. Coons (D), 2022-05-03

³ Example for story of rising: "I consider protecting our God-given right to life as one of my most important responsibilities. I have fought back against Dems challenges to the pro-life message by opposing taxpayer funded abortions & protecting healthcare providers who do not perform abortions." Mike Simpson (R), 2022-03-05

about abortion on social media. Specifically, this research analyzes whether and how the overturning has influenced the types of stories—in particular, stories of decline and stories of rising—that these political actors employ to frame the issue of abortion and whether these narrative shifts vary by party affiliation, geographic location based on state-level abortion laws, and the immediacy of the leaked draft versus the actual judicial decision.

H0: No effect of the overturning of Roe v. Wade on the story types used in narratives by US representatives on Twitter

The null hypothesis posits that the overturning of Roe v. Wade has not resulted in any relevant changes in the types of narratives employed by US representatives when discussing abortion on social media.

H1: Democrats and Republicans exhibited different adjustments in their story types after the overturning.

Hypothesis 1 is predicated on the significant polarization in American political discourse surrounding abortion. The sharp ideological divide between Democrats and Republicans is vividly reflected in their respective narratives on abortion, mirroring broader societal divisions and influencing political behaviors and alignments. This divergence is rooted in fundamentally different framing strategies employed by the two parties—the “pro-life” strategy predominantly used by Republicans and the “pro-choice” one used by Democrats—each filled with deep moral, ethical, rights-based, health, and religious undertones (Adams 1997; Carmines and Woods 2002; Carsey and Layman 2006; Killer and Wilcox 2008).

A special focus will be set on tweets by Republicans and the adjustments to their story types. Following the “pro-life” stances of the conservative parties, an increase in stories of rising would be anticipated. However, Republicans could also recalibrate their narrative approach to incorporate more stories of decline rather than framing the event as a straightforward victory. This strategic shift in narrative is rooted in the understanding that a significant portion of the electorate supports the constitutional right to abortion. Aware of this public sentiment, Republicans could add nuance to their storytelling to better align with the broader preferences of voters, possibly emphasizing the potential negative implications and societal impacts of the overturning.

H2: Geographic variability in narrative shifts based on state-level abortion policies.

Hypothesis 2 explores the influence of geographic variability on narrative shifts, particularly focusing on Republican representatives from states with trigger laws that immediately outlawed abortion following the overturn of Roe v. Wade. It posits that in these states, Republicans increasingly employed stories of decline in their narratives. This strategic choice acknowledges the immediate impact of the overturning on the voters, whose access to abortion was directly affected, potentially

altering their voting behaviors in the midterm elections. Recognizing the significance of public sentiment towards abortion access, this hypothesis suggests that Republican narratives were adjusted to resonate with voters who favor maintaining abortion rights despite the enactment of restrictive state-level policies. This study represents a significant contribution to the fields of political science and political communication, particularly through its innovative approach to analyzing political narratives surrounding the highly contentious issue of abortion in the United States. By employing machine learning to classify story types in US representatives' narratives on social media, this research advances the application of the Narrative Policy Analysis. Lastly, the study provides empirical evidence of how political narratives evolve in response to landmark legal changes.

4. Data & Methodology

This section describes the methodological foundations of this study. It outlines the systematic approach for data collection, the classification of tweets, the operationalization of key variables, and the analytical methods employed. It explains the processes behind assembling the dataset, the rationale for the chosen methods, and the robustness checks that support the study's findings.⁴

4.1. Data Compilation and Supervised Text Classification

4.1.1. Data Collection

To compile the study's dataset, I employed a systematic data collection process that involved the following steps: First, I created a list of all House and Senate representatives who had an active Twitter account in December 2022. For this, I used the *Members' Official Twitter Handle dataset* provided by the U.S. House of Representatives Press Gallery (Press Gallery 2023), which contained information on 437 House and 100 Senate representatives. I created a list of their names, Twitter handles, representation in Congress or Senate, party affiliation, and which state they represent. Second, I scraped all tweets by the identified representatives in the year 2022 using the Twitter application programming interface (API) (Twitter 2023). The search criteria specified a date range from Jan 1, 2022, to Dec 31, 2022, resulting in 369,477 tweets. Finally, I performed data cleaning to remove retweets and duplicates from the dataset and filtered it to include tweets that contained the word *abortion*. Since the number of independent representatives was extremely small and the study mainly focused on the partisan aspect of Democrats and Republicans, tweets by independent representatives were excluded. The dataset was thus reduced to

⁴ All code created for the analyses in this study, including web scraping of the data, training the classifier model and the models for analyses, has been implemented in the programming language R. The complete code is available on a GitHub repository, which can be accessed here: [anonymized]

5,293 tweets. This process ensured that the analysis focused solely on original tweets posted by the House and Senate representatives about abortion. Information about states that had so-called trigger laws in place was acquired through the Wikipedia entry on *trigger laws* (Wikipedia 2023) and included in the dataset. **Figure 1** illustrates the daily volume of tweets by party throughout 2022 including key events related to abortion.

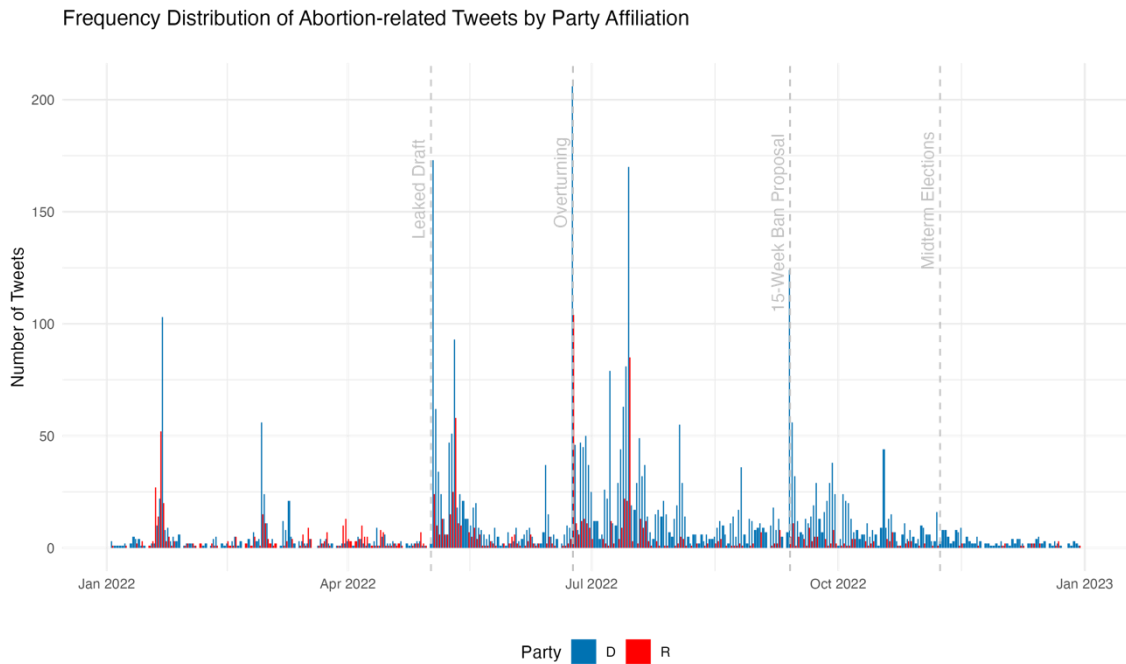


Figure 1: Frequency distribution of abortion-related tweets by U.S. representatives, distinguishing between Democratic (blue) and Republican (red) party affiliations throughout 2022. Key events are annotated and marked with vertical dashed lines: the leaked draft opinion (May 2), the overturning of *Roe v. Wade* (June 24), the 15-week abortion ban proposal (September 13), and the midterm elections (November 8).

4.1.2. Classification of Tweets through Machine Learning

In order to obtain the story type of the tweets, a machine learning approach was conducted. Supervised text classification can automatically extend manual coding to a large number of texts. This machine learning technique identifies word patterns that define various classes and then apply these patterns to categorize new texts that have not been analyzed before (Macanovic 2022). The technique predicts labels on text documents using a model to classify what type of narrative the tweets are. Following a tidy model approach for supervised machine learning for text analysis in R (Hvitfeldt and Silge 2022; Kuhn and Silge 2023), the text classification involved several steps. First, I manually annotated a subset of the dataset (365 tweets) according to the story type categories as outlined by Stone (2012). The binary factor outcome variable “story type” has two levels, story of decline and story of rising. A story of decline is a narrative that portrays a worsening situation or negative

consequences related to abortion policies. This is an example of a story of decline from the dataset: “Should this decision become law, roughly half the states in our country will make all or nearly all abortions illegal, leading to gross inequalities in health care access.” Christopher A. Coons (D), 2022-05-03

In contrast, a story of rising is a narrative focusing on successful efforts to regulate, manage, or exert authority over abortion policies. An example of a story of rising from the dataset is the following: “I consider protecting our God-given right to life as one of my most important responsibilities. I have fought back against Dems challenges to the pro-life message by opposing taxpayer funded abortions & protecting healthcare providers who do not perform abortions.” Mike Simpson (R), 2022-03-05

The manually annotated dataset is then split into training and testing data sets to evaluate the model's performance on unseen data.

The next step specified how to process the data before modeling. This involved tokenizing the text (breaking it down into words or tokens), removing common but uninformative words known as stopwords, filtering tokens to keep only the most relevant ones, and calculating term frequency-inverse document frequency (TF-IDF) values. TF-IDF is a statistical measure used to evaluate how important a word is to a document in a collection of documents, helping to adjust for the fact that some words appear more frequently in general.

Then, I specified the model as a Support Vector Machines (SVM) model with a polynomial kernel. At its core, an SVM aims to find the best separating boundary between different classes of data points in a given feature space (Kuhn and Vaughan 2024). The "best" boundary is the one that maximizes the margin between the nearest points of the classes, which are known as support vectors. The polynomial kernel helps capture the interaction between features to a certain degree, as specified by the kernel's parameters.

A workflow then combines the preprocessing steps and the model specification. Here, a 5-fold cross-validation is prepared on the training data to help estimate the model's performance and tune model parameters. Next, the SVM model is fit on the entire training dataset to prepare it for making predictions on new, unseen data. After fitting the model, it is used to predict outcomes on the test set. The predictions are then bound to the original test set data for evaluation. Predictions include the probabilities of each class (story of rising vs. story of decline), from which a binary classification is derived based on a threshold (0.5). Evaluation involves calculating accuracy, recall (sensitivity), and precision.

The last step is to use this model to make predictions on the entire dataset. With this dataset in place, I can analyze the narratives employed by House and Senate representatives before and after the overturning of Roe vs. Wade, shedding light on

how political discourse around abortion policy has evolved in response to this significant legal event.

Upon training, the SVM model with a polynomial kernel demonstrated robust performance on the validation data, with the following metrics (see **Table A1** in the Appendix): The accuracy of 0.71 indicates that the model correctly predicted the story types for 71% of the tweets in the validation set. The recall of 0.76 suggests that it successfully identified 76% of all relevant instances, which is crucial for applications where missing a positive instance can have significant consequences. The precision of 0.71 means that 71% of instances classified as positive were indeed correct, balancing the cost of false positives against the need for accurate positive detection. These metrics collectively show that the SVM classifier performs competently in distinguishing between different story types.

The study also evaluated the performance of various predictive models. In the appendix is a summary table of the performance metrics across nine different models (**Table A1**). When compared to a range of other classifiers tested, the SVM model stands out for its balanced performance. The model not only matches the highest accuracy seen in other models but also provides competitive recall and precision rates. It surpasses models like the decision tree in accuracy and maintains higher precision than the nearest neighbor model, which, despite its high recall, suffers from low precision indicative of a high false positive rate.

4.2. Methodological Framework

4.2.1. Operationalization of Variables

In the analysis, I used several key variables, which I will explain below. The variable “story type binary” is a binary indicator, set to 1 for tweets categorized as *stories of decline* based on the predicted story type and 0 for *stories of rising*.

The binary variable “overturn” indicates the post-legislative change period, coded as 1 from June 24, 2022, onward. The temporal context is further detailed by the variable “events,” which classifies the timeline into five distinct phases, each representing a critical period in the political and legal discourse around abortion in 2022: before the leaked opinion draft (January 1–May 1), between the leak and the overturning of *Roe v. Wade* (May 2—June 23), between the overturning and the proposed 15-week abortion ban bill (June 24–September 12), between the bill and the midterm elections (September 13–November 7) and after the elections (November 8–December 31).

Additional variables such as “name,” “party,” and “state” refer to the individual characteristics of the representative. The binary variable “state trigger law” identifies states with trigger laws and is set to 1 if there is a trigger law. “Date numeric” offers a continuous scale representation of dates.

4.2.2. Analytical Methods

Various statistical methods were used for the empirical testing of the hypotheses. The selection comprises one logistic regression, five generalized linear mixed models, and one generalized additive model.

The logistic regression (Model 1) serves as an initial analysis for investigating the influence of the overturning on the probability of narratives being characterized as a story of decline. Logistic regression is suitable for binary dependent variables, as is the case with the story types.

Recognizing the clustering of data points within individual representatives, the analysis further uses generalized linear mixed models (GLMM) (Models 2-6) with random intercepts. This method addresses the dependencies among observations stemming from the same individual, providing a more nuanced capture of the heterogeneity in story types (Agresti 2018). Through random effects, these models correct for the possible inflation of type I error rates that might occur due to repeated measures from the same subjects, enhancing the validity of the statistical inferences.

Focusing on the temporal aspect, a generalized additive model (GAM) sheds light on the trends in the data over time (Agresti 2018). The model's flexibility is important in adapting to the potential non-linear trajectories that the narratives take across key political events.

4.3. Statistical Modelling and Validation

4.3.1. Model Specification

As described, I employed a series of statistical models. Below is a detailed overview of each model utilized in the study: First, the analysis included a logistic regression model (Model 1), which directly measured the impact of the overturning of Roe v. Wade on the story types. The model identified whether a tweet falls under story of decline using the binary outcome variable "story type binary." The key predictor, "overturn," captured the temporal effect by indicating if a tweet was posted after the legal change.

Second, to account for the non-independence of tweets by the same representatives and over time, a series of GLMMs were deployed (Models 2, 4-6): Model 2 incorporated "events" as a fixed effect and "name" as a random intercept, which enabled the differentiation of narrative shifts across distinct political timelines. Models 4 and 5 further examined the interactions between political affiliation ("party") and key events ("events"). Model 4 addressed the whole representative sample, while Model 5 focused specifically on Republican narratives.

Model 4 is one of two key models and can be specified as follows:

$$\text{logit} \left(P(Y_{ij} = 1) \right) = \beta_0 + \beta_1 * (\text{Party})_{ij} + \beta_2 * (\text{Events})_{ij} + \beta_3 * (\text{Party} \times \text{Events})_{ij} + u_j$$

- Y_{ij} is the binary response variable, which indicates the type of narrative used by the representative j in tweet i , with 1 for a story of decline and 0 a story of rising.
- The logit link function is employed to model the probability P that $Y_{ij} = 1$, representing the odds of a tweet being a story of decline.
- β_0 denotes the intercept, or the baseline log odds of a story being a story of decline when all explanatory variables are zero.
- β_1 captures the effect of a representative's party affiliation on the log odds of the narrative being a story of decline.
- β_2 represents the impact of the specific time periods associated with the abortion debate on the log odds of the story type.
- β_3 is the interaction term coefficient, which examines how the effect of party affiliation on the narrative type varies across the different periods.
- u_j is the random intercept for each representative, which accounts for the variability in story type usage that is not explained by the fixed effects in the model. This term acknowledges that each representative may have a unique propensity to use decline narratives that could bias the fixed effect estimates if not properly modeled.

The coefficients β_1 , β_2 , and β_3 are interpreted in terms of odds ratios upon exponentiation. An odds ratio greater than 1 indicates an increased likelihood of a story being a story of decline, while an odds ratio less than 1 indicates a decrease. The interaction term, in particular, allows us to understand if and how party affiliation modifies the relationship between the events and the type of narrative employed. By including a random intercept u_j , I account for the within-representative correlation, recognizing that tweets from the same individual are likely to be more similar to each other than to tweets from different representatives. Models 6 and 7 evaluate the influence of geographical variations through “state trigger law.” Model 7 is particularly complex, including interactions between “state trigger law,” “events,” and “party,” thus examining the combined effects of legal, temporal, and partisan factors on narrative construction.

Model 7 is the other key model and is specified as follows:

$$\text{logit} \left(P(Y_{ij} = 1) \right) = \beta_0 + \beta_1 * (\text{State Trigger Law})_{ij} + \beta_2 * (\text{Events})_{ij} + \beta_3 * (\text{Party})_{ij} + \beta_4 * (\text{State Trigger Law} \times \text{Events})_{ij} + \beta_5 * (\text{State Trigger Law} \times \text{Party})_{ij} + u_j$$

- Y_{ij} is the binary response variable indicating the type of narrative used by the representative j in tweet i , with 1 for a story of decline and 0 a story of rising.
- The logit link function is employed to model the probability P that $Y_{ij} = 1$, representing the odds of a tweet being a story of decline.
- β_0 denotes the intercept, or the baseline log odds of a story being a story of decline when all explanatory variables are zero.

- β_1 measures the effect of the presence of state trigger laws on the log odds of the narrative being a story of decline.
- β_2 captures the impact of key events associated with the abortion debate on the log odds of the story being a story of decline.
- β_3 indicates the influence of the representative's party affiliation on the log odds of the story being a story of decline.
- β_4 is an interaction term that examines how the influence of state trigger laws on story type varies across different periods.
- β_5 is another interaction term, which assesses how the effect of party affiliation on the narrative type is modified in the presence of state trigger laws.
- u_j is the random intercept for each representative, accounting for the variability in story type usage that is not explained by the fixed effects in the model.

Furthermore, to explore the non-linear temporal dynamics in narrative adoption, a GAM is employed (Model 3). This model features a smooth term for "date numeric" to flexibly model time, alongside "events," "party," and "state trigger law," offering a detailed look at how narrative types evolve in response to unfolding political events.

4.3.2. Robustness Checks and Model Assumptions

To ensure the validity and reliability of the findings from this study, it is essential to rigorously test the robustness of the models used and verify that they meet the necessary statistical assumptions. Focusing on the two key models central to the main analysis, I will explore how Models 4 and 7 perform under various conditions and assess their stability through robustness checks. Additionally, I will examine the fundamental assumptions underpinning the models to confirm that the interpretations and conclusions are well-supported by the data.

In order to assess the stability and reliability of the coefficients estimated by Models 4 and 7, I conducted a nonparametric bootstrap analysis with 1,000 replications (see **Table A2** and **A3** in the appendix). The bootstrap method provided a re-sampling distribution for each coefficient, allowing me to estimate standard errors and biases for the original parameter estimates (Huntington-Klein 2022). The results indicated that the original coefficients were robust, with biases that were small in magnitude relative to the standard errors, suggesting little influence on the stability of the model estimates. For example, the largest bias observed in Model 4 was for the interaction term *R * Between Bill and Midterm Elections*, with an estimate of 0.078, but even this remained small compared to its standard error of 0.209. Similarly, the standard errors ranged from 0.102 for the intercept to 0.586 for *After the Midterm Elections*, reflecting the varying levels of precision in the coefficient estimates. These bootstrap-derived standard errors provide an additional layer of validation for the interpretability and reliability of the models' findings.

Ensuring the integrity of the findings requires a thorough examination of the assumptions underlying the statistical models used in this study. For this, checks were performed for overdispersion, random effects structure, and residuals for the two key generalized linear mixed models (GLMMs), Models 4 and 7.

Overdispersion occurs when the observed variance in the data is higher than the variance predicted by the model under the assumption of a given error distribution (Gelman and Hill 2006). It can lead to underestimating the standard errors of the model's estimates, which in turn inflates Type I error rates and leads to overly confident conclusions. Checking for overdispersion is, therefore, crucial to ensure the reliability of the model's inferences.

Overdispersion checks were performed for both Models 4 and 7 (see **Table A4** in the appendix). The checks involved calculating the ratio of the sum of squared Pearson residuals to the residual degrees of freedom, yielding values of approximately 0.958 for Model 4 and 0.959 for Model 7. These results indicate an absence of significant overdispersion, confirming that the variance structures assumed by the models are appropriate for the data. This means that the standard errors of the estimates are reliable, and thus, the statistical tests and confidence intervals derived from these models are likely to be valid.

In assessing the need for random effects in my models, analysis of variance (ANOVA) tests were conducted to compare generalized linear mixed models (GLMMs) with their generalized linear model (GLM) counterparts (see **Tables A5** and **A6** in the appendix) (Agresti 2018). For Model 4, significant improvements in model fit were observed with the inclusion of random effects for representatives, as evidenced by reduced deviance in models incorporating interactions between "party" and "events" ($p < 0.001$). Similarly, for Model 7, while the main effects involving "state trigger law" did not significantly enhance the model, interactions with "events" did, indicating a nuanced influence on the response variable that is better captured with mixed-effects modeling.

Residual diagnostics for Models 4 and 7 were conducted to validate the fit and assumptions underlying the mixed-effects modeling approach (see **Figures A1** and **A2** in the appendix). The Quantile-Quantile plots for each model exhibited a strong alignment of residuals with the expected normal distribution, confirmed by Kolmogorov-Smirnov tests yielding p-values of 0.76 and 0.696 for Models 4 and 7, respectively. This indicates no significant departure from normality in the distribution of residuals for either model.

In addition to the normality assessments, plots comparing residuals to the models' predicted values were examined for any discernible patterns that could indicate issues such as non-linearity or heteroscedasticity. For both models, no such patterns were observed, and the residuals appeared randomly scattered around zero without any systematic deviations across the range of predictions. This randomness is

further supported by non-significant p-values in dispersion tests (both $p = 0.9$) and outlier tests ($p = 0.394$ for Model 4 and $p = 0.48591$ for Model 7), suggesting that the variance of the residuals is well captured by the models and that there are no more outliers than would be expected by chance.

These comprehensive diagnostic checks reinforce the suitability of the random effects structure employed in both models and underpin the validity of the assumptions integral to my mixed-effects modeling approach. Collectively, the results affirm my confidence in the robustness and predictive capability of the GLMMs, providing a strong foundation for the reliable interpretation of the factors influencing the types of narratives in tweets as modeled by my study.

The Data and Methods section has detailed the processes for data collection, classification, and analytical methods used to investigate the narratives related to abortion on Twitter. The subsequent section will present the results of these analyses, showcasing the insights gained from the application of these methods.

5. Results

This section illustrates the empirical findings related to the study's hypotheses. First, I examine the impact of the overturning on story types; second, I evaluate whether Republicans and Democrats displayed different narrative shifts; and third, I assess the geographical variability in narrative shifts influenced by state-level abortion policies. The results clearly show highly significant effects across all examined hypotheses. Notably, the leaked draft acted as a catalyst, prompting a noticeable increase in stories of decline across party lines, with Republicans demonstrating a pronounced shift in their narrative strategy. Additionally, the influence of state-level trigger laws on narrative strategies proved to be more multifaceted than initially hypothesized, revealing complex interactions with temporal factors that underscore the localized complexities of political communication.

5.1. Impact of Overturning *Roe v. Wade*

The first analysis systematically challenged the null hypothesis that the overturning of *Roe v. Wade* would leave the narrative strategies of U.S. representatives on Twitter unchanged. I utilized a basic logistic regression model (1) and a generalized linear mixed model (2) to explore this. As shown in **Table 1**, the key variable in the logistic regression model was "overturn." The results indicated that the log odds of a U.S. representative using a story of decline in their Twitter narrative increased significantly by 0.14 ($p = 0.012$) following the overturning, compared to the reference period before the judicial decision. Since the log odds ratio given is in natural logarithm form (log base e), to convert this to an odds ratio, we need to raise the mathematical constant e (ca. 2.72) to the power of the log(OR) value. In other words, we need to raise 2.72 to the nth power of the log(OR) value, i.e. $2.72^{0.14} \approx 1.15$.

This means that the odds of a U.S. representative tweeting a story of decline are about 1.15 times higher after the overturning than before.

Characteristic	Logistic Regression Model (1)		Generalized Linear Mixed Model (2)	
	log(OR) (95% CI) [†]	p-value	log(OR) (95% CI) [†]	p-value
overturn				
0	—			
1	0.14 (0.03 to 0.25)	0.012		
No. Obs.	5,288		5,288	
events				
Before Leak	—			
Between Leak and Overturning			0.56 (0.37 to 0.75)	<0.001
Between Overturning and Bill			0.37 (0.20 to 0.54)	<0.001
Between Bill and Midterm Elections			0.70 (0.50 to 0.90)	<0.001
After the Midterm Elections			0.27 (-0.08 to 0.62)	0.13

[†] OR = Odds Ratio, CI = Confidence Interval

Table 1: Comparative analysis of narrative strategies pre- and post-overturning of Roe v. Wade. The table displays the log odds ratios (log(OR)) and confidence intervals (CI) for the likelihood of U.S. representatives on Twitter using stories of decline narratives during different time periods in 2022. The logistic regression model (1) evaluates the isolated effect of the overturning, while the GLMM (2) assesses the impact across distinct time intervals, taking into account the within-representative correlation. Statistical significance is denoted by p-values, with values less than 0.05 indicating a statistically significant difference from the baseline period before the overturning or leak.

The GLMM (2) captured the complexity of these narrative shifts in more detail, taking into account more than the isolated event of the overturning and instead including periods between key events related to the overturning of Roe v. Wade. Correspondingly, the plot in **Figure 2** illustrates the estimated marginal effects of the GLMM. Each point on the plot denotes the estimated effect size for a particular time period, with vertical lines representing 95% confidence intervals. Starting from before the leak, we observe a lower estimated effect, suggesting that stories of decline were less likely to be used in narratives. The period after the leak and before the overturning saw a strong increase in the likelihood of stories of decline (log(OR) = 0.56, $p < 0.001$), indicating a significant rise in the usage of decline narratives coinciding with the leaked opinion draft. The phase between the overturning and the proposal of the 15-week abortion ban bill (referred to as “bill”) continued to show a higher, albeit reduced, probability of decline narratives (log(OR) = 0.37, $p < 0.001$). Interestingly, the period leading up to the midterm elections witnessed the highest uptick in decline narratives (log(OR) = 0.70, $p < 0.001$). This means the odds of a tweet being a story of decline increased 2-fold ($2.72^{0.7} \approx 2.01$) compared to before the leak. However, after the midterm elections, the log odds of 0.27, with a wide confidence interval indicating higher levels of uncertainty, did not reach the level of significance ($p = 0.13$).

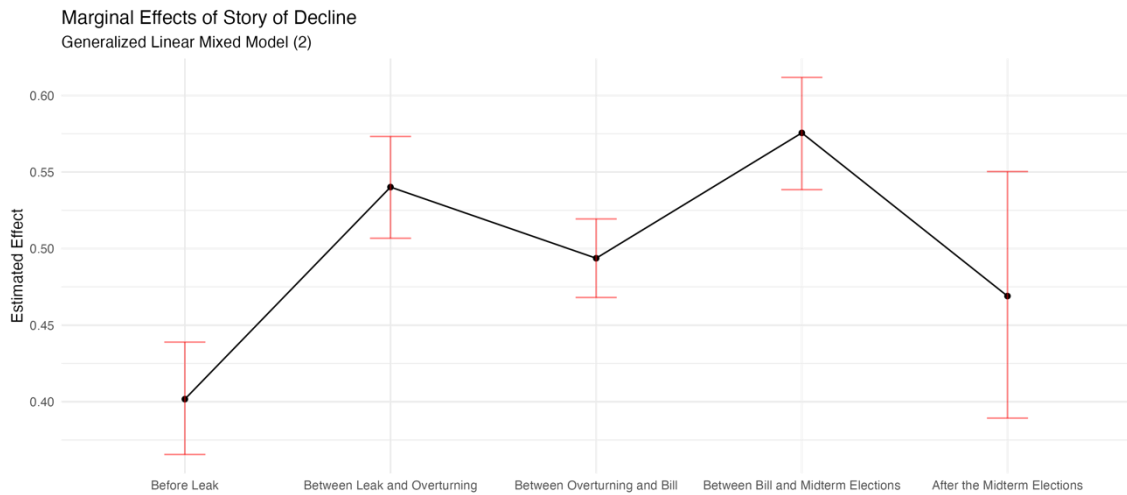


Figure 2: Marginal effects of GLMM (2) on narrative types. This figure illustrates the estimated probabilities of U.S. representatives on Twitter using stories of decline at various key periods in 2022. The black line indicates the estimated marginal effect (the probability of using a decline narrative), while the red vertical error bars represent the 95% confidence intervals for each estimate. The data points show a distinct temporal pattern in narrative usage, with peaks and troughs aligning with significant political events such as the leaked draft, the overturning of *Roe v. Wade*, the proposal of a 15-week abortion ban bill, and the midterm elections.

As it became clear that narrative strategies of U.S. representatives using stories of decline fluctuated in relation to key events in 2022, I next wanted to understand the temporal dynamics of these shifts better. A generalized additive model (GAM) incorporating date and events clearly reveals these shifts (**Figure 3**). The plot of fitted values from the GAM model describes the changing landscape of story of decline probabilities over time. The dashed vertical lines correspond to the four pivotal events. Prior to the leaked draft, the fitted values indicated a relatively low but stable probability of decline narratives. However, there was a significant escalation, coinciding with the leak on May 2, 2022, with the fitted probability cresting. This surge underscores the immediate impact of the leak on narrative approaches. The official overturning on June 24, 2022, marks another notable spike. The subsequent proposal of the 15-week abortion ban bill on September 13, 2022, pushed these narratives even further toward stories of decline. Interestingly, the model reveals a pronounced drop around the midterm elections on November 8, 2022. Post-elections, the fitted values bounce back increasing again the probability for stories of decline.

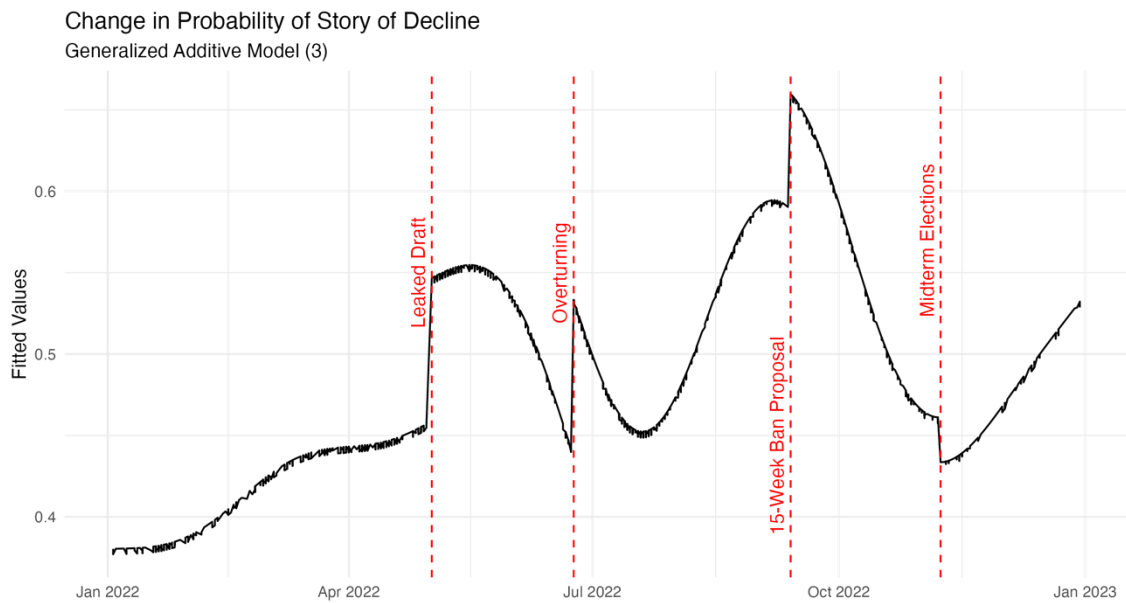


Figure 3: Temporal dynamics in the probability of story of decline narratives used by U.S. representatives. The graph depicts the fitted probabilities derived from a GAM (3) over time, highlighting shifts in narrative strategy before and after critical junctures in the abortion debate of 2022. Dashed red lines mark the dates of the leaked opinion draft (May 2), the overturning of *Roe v. Wade* (June 24), the 15-week abortion ban proposal (September 13), and the midterm elections (November 8).

5.2. Partisan Differences in Narrative Strategies

The next hypothesis postulated that Democratic and Republican representatives would exhibit distinct narrative adjustments after the overturning, reflective of their ideological stances on abortion. I utilized two generalized linear mixed models to explore these potential partisan divergences (**Table 2**).

The results of the model with both parties (4) indicated that, compared to Democrats (the reference category), Republicans are less likely to use stories of decline in their narratives on a highly significant level ($\log(\text{OR}) -0.46, p = 0.004$). The events factors account for changes in narrative strategies across different time periods. These coefficients represent the log odds of using stories of decline in reference to the baseline category (“Before Leak”). This analysis revealed an increase in the probability of employing stories of decline for the time between the leak and the overturning ($\log(\text{OR}) = 0.31, p = 0.008$) and even more between the bill proposal and the midterm elections ($\log(\text{OR}) = 0.59, p = p < 0.001$). The interaction term captures how the effect of being a Republican representative on the probability of using stories of decline varies across the different time periods. Republicans showed a significant increase in the likelihood of using stories of decline narratives after the leak but before the overturning ($\log(\text{OR}) = 0.74, p < 0.001$). Furthermore, this trend continued for the time between the overturning and the bill proposal ($\log(\text{OR}) = 0.72, p < 0.001$). However, after the bill proposal, no significant effects were observed. Still,

the interaction effects were crucial in this model because they demonstrated that the changes in story types were not uniform for both parties over time. The coefficients of the interaction terms for Republicans notably differ from the main effects of time periods.

Characteristic	GLMM (4)		GLMM Republicans (5)	
	log(OR) (95% CI) ¹	p-value	log(OR) (95% CI) ¹	p-value
party				
D	—			
R	-0.46 (-0.78 to -0.15)	0.004		
events				
Before Leak	—		—	
Between Leak and Overturning	0.31 (0.08 to 0.54)	0.008	1.1 (0.71 to 1.4)	<0.001
Between Overturning and Bill	0.14 (-0.07 to 0.35)	0.19	0.87 (0.56 to 1.2)	<0.001
Between Bill and Midterm Elections	0.59 (0.36 to 0.83)	<0.001	0.45 (-0.03 to 0.92)	0.065
After the Midterm Elections	0.12 (-0.27 to 0.50)	0.55	0.36 (-0.59 to 1.3)	0.46
party * events				
R * Between Leak and Overturning	0.74 (0.32 to 1.2)	<0.001		
R * Between Overturning and Bill	0.72 (0.35 to 1.1)	<0.001		
R * Between Bill and Midterm Elections	-0.14 (-0.67 to 0.39)	0.60		
R * After the Midterm Elections	0.25 (-0.77 to 1.3)	0.63		
No. Obs.	5,288		1,197	

¹ OR = Odds Ratio, CI = Confidence Interval

Table 2: Comparative analysis of narrative types in response to key events by party affiliation using generalized linear mixed models. This table presents the findings from the GLMM with both parties (4), which assesses narrative changes over time and includes the interaction effects of party affiliation and key events. The second GLMM (5) is based on a subset of the data that only includes the effect of key events on Republicans' narratives. The table displays the estimated log odds ratios (log(OR)), confidence intervals (95% CI), and p-values for the significance of each effect, with observations (No. Obs.) reflecting the sample size for the analysis.

The accompanying plot (**Figure 4**) illustrates these findings: it contrasts the predicted probabilities of narrative strategies employed by Democrats and Republicans. Prior to the leaked draft opinion, the probability of employing a story of decline narrative was relatively low for both parties. However, with the leaked draft and the ensuing political and societal turmoil, there was a steep increase for Republicans. Notably, the period between the bill proposal and the elections saw an increase in stories of decline narratives for Democrats. Following the bill proposal, there was a further decrease for Republicans. After the midterms, both parties display a downward trend in the predicted probability of stories of decline, albeit the trend was more pronounced for Republicans.

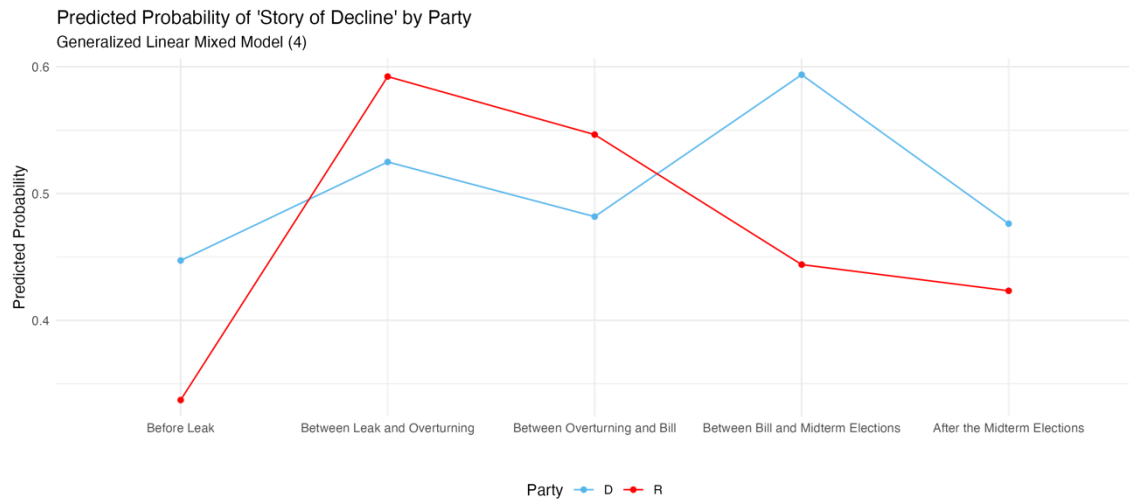


Figure 4: Trajectory of narrative types by the political party. This figure illustrates the predicted probabilities of employing stories of decline narratives by Democrats (D) and Republicans (R) at different time intervals surrounding the key events related to Roe v. Wade's overturning. It visualizes the comparative analysis based on the GLMM of both parties (**Table 2 (4)**) and highlights the significant shifts in narrative types before and after the leak, the overturning, the bill proposal, and following the midterm elections.

To get an even deeper understanding of the partisanship aspect, a separate generalized linear mixed model (5) was calculated including only Republican representatives (**Table 2**). For Republicans, the period between the leaked draft and the overturning of Roe v. Wade is characterized by a highly significant chance of using stories of decline compared to the reference category before the leak ($\log(\text{OR}) = 1.1, p < 0.001$). Still, between the overturning and the bill proposal, the increased likelihood of stories of decline continued to be significant ($\log(\text{OR}) = 0.87, p < 0.001$). This narrative thrust appears to maintain its momentum between the overturning and the bill proposal, albeit with a slight decrease ($\log(\text{OR}) = 0.87, p < 0.001$). Interestingly, the period after the bill proposal and after the midterm elections did not display a statistically significant shift in narrative probability ($\log(\text{OR}) = 0.45, p = 0.065$ and $\log(\text{OR}) = 0.36, p = 0.46$).

5.3. Geographic Variability of Story Types Based on Trigger Laws

The last hypothesis of the study accounts for the geographical variability in the narrative strategies of U.S. representatives, specifically in relation to state-level trigger laws activated by the overturning of Roe v. Wade. After analyzing density plots of the proportion of stories of decline based on state-level trigger law status, I applied two generalized linear mixed models to investigate the complexities inherent in the geographic variations. The analyses revealed significant geographic variability in the narrative strategies of U.S. representatives, showing that state-level trigger laws, especially in interaction with key events, significantly influenced the use of decline narratives on Twitter.

A series of density plots (**Figure 5**) illustrate the variations in the proportions of story of decline across the different time phases relative to a state's trigger law status. The density plots offer a visual comparative analysis, illustrating how the presence of a trigger law (denoted by 1 in yellow) versus its absence (denoted by 0 in purple) correlates with the proportion of decline narratives within the states. The x-axis of each plot represents the proportion of story of decline, ranging from 0 (no stories of decline) to 1 (all stories reflect decline). The y-axis signifies the density, which corresponds to the probability of a given proportion of story of decline. In essence, the y-axis helps us understand the relative frequency of the data points; higher peaks indicate a higher concentration of states with a particular proportion of decline narratives. The first plot, "Before Leak," displays a bimodal distribution. This means that there are two distinct peaks, suggesting that there are two prevailing groups regarding the story of decline narrative: states with trigger laws, with a low proportion of decline narratives, and states without trigger laws, with a high proportion. Furthermore, the distinction in density peaks between the categories with and without trigger laws is indicative of the various impact that such laws may have on states. For instance, in the phase "Between Overturning and Bill", we observe a pronounced disparity, where the density for states without trigger laws peaks at a significantly higher level than for those having trigger laws.

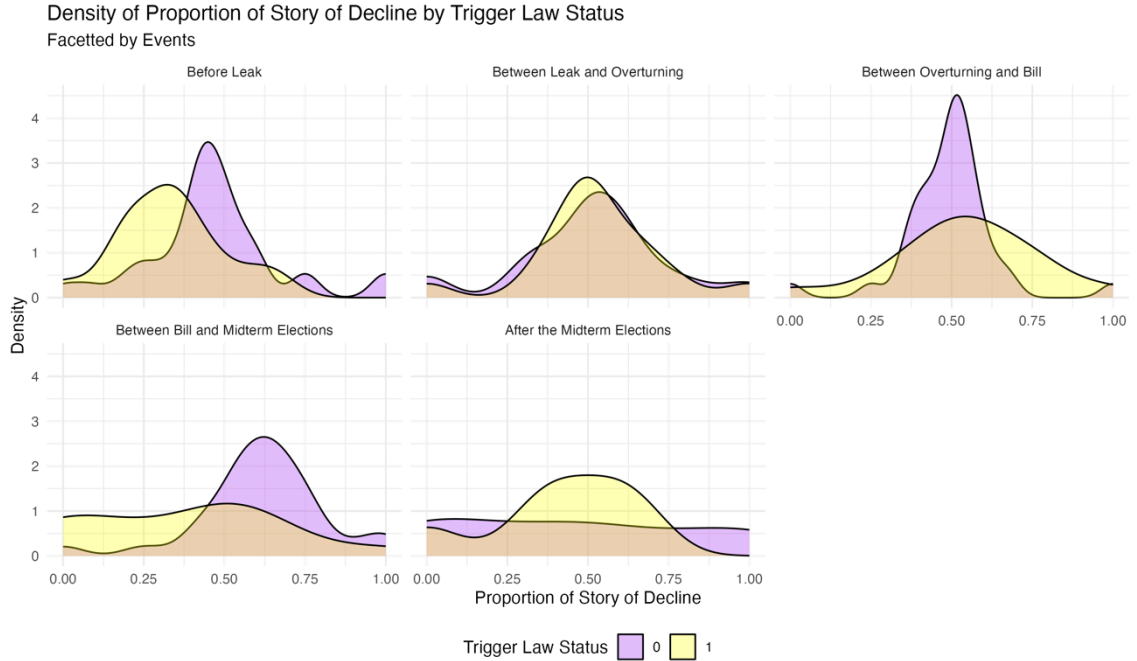


Figure 5: Density distribution of story of decline narratives by trigger law status across different time periods. This set of density plots represents the proportion of story of decline narratives used by U.S. representatives in states with trigger laws (denoted by 1 in teal) and without (denoted by 0 in red), across five distinct time periods surrounding the overturning of Roe v. Wade. The plots highlight the

variations in narrative use before and after the leaked draft, the overturning, the bill proposal, and following the midterm elections.

Two generalized linear mixed models (Table 3) were used to quantitatively analyze the effect of the trigger law status on the story types. The GLMM without interaction terms (6) generated an interesting result: The mere existence of a trigger law had no direct effect on the narrative types ($\log(\text{OR}) = 0.00$, $p = 0.96$). This finding initially seems to counter the anticipated influence of such legislation on narrative strategy. However, the analysis becomes significantly more textured when state trigger laws are considered in interaction with events in the following model (7). Compared to the baseline period “Before Leak” in states without trigger laws, representatives from states with trigger laws were significantly more likely to use stories of decline following the leak leading up to the overturning ($\log(\text{OR}) = 0.52$, $p = 0.027$). This trend was further amplified between the overturning and the introduction of the bill, where the likelihood of using decline narratives increased even more ($\log(\text{OR}) = 0.70$, $p < 0.001$). In contrast, there was no significant interaction effect between state trigger law and party affiliation ($\log(\text{OR}) = -0.16$, 95% CI: -0.60 to 0.28, $p = 0.48$).

Characteristic	GLMM (6)		GLMM with Interactions (7)	
	$\log(\text{OR})$ (95% CI) [†]	p-value	$\log(\text{OR})$ (95% CI) [†]	p-value
state_trigger_law				
0	—		—	
1	0.00 (-0.21 to 0.22)	0.99	-0.31 (-0.78 to 0.16)	0.20
period_factor				
Before Leak	—		—	
Between Leak and Overturn	0.56 (0.37 to 0.75)	<0.001	0.44 (0.22 to 0.65)	<0.001
Between Overturn and Bill	0.37 (0.20 to 0.54)	<0.001	0.22 (0.03 to 0.41)	0.024
Between Bill and Elections	0.70 (0.50 to 0.91)	<0.001	0.65 (0.43 to 0.88)	<0.001
After the Midterm Elections	0.27 (-0.08 to 0.63)	0.13	0.20 (-0.18 to 0.58)	0.31
party				
D	—		—	
R	0.00 (-0.20 to 0.19)	0.96	0.03 (-0.20 to 0.26)	0.78
state_trigger_law * period_factor				
1 * Between Leak and Overturn			0.52 (0.06 to 0.98)	0.027
1 * Between Overturn and Bill			0.70 (0.29 to 1.1)	<0.001
1 * Between Bill and Elections			-0.03 (-0.58 to 0.52)	0.92
1 * After the Midterm Elections			0.18 (-0.81 to 1.2)	0.72
state_trigger_law * party				
1 * R			-0.16 (-0.60 to 0.28)	0.48

[†] OR = Odds Ratio, CI = Confidence Interval

Number of observations: 5288

Table 3: Comparative analysis of generalized linear mixed models with (6) and without interaction terms (7). The table presents the results of the GLMM without interaction terms (6), which analyzed the effect of trigger law status on story types, taking into account the time periods surrounding key events and party affiliation of the representatives. The second model (7) includes interaction effects, which take into account the interaction between the trigger law status and the time periods and

between the trigger law status and the party affiliation. The table includes the log odds ratios ($\log(\text{OR})$) with 95% confidence intervals (CI) and the number of observations (No. Obs.) and indicates significant results where the p-value is less than 0.05.

Concluding the analysis, this study shed light on the significant ways in which political narratives on Twitter have evolved in response to the landmark judicial decision to overturn *Roe v. Wade*. My results rejected the null hypothesis clearly and showcased highly significant effects across all examined hypotheses. Furthermore, we observed that the leaked draft acted as a catalyst, initiating a noticeable increase in stories of decline across party lines, with Republicans demonstrating a pronounced pivot in their narrative strategy. Geographically, the influence of state-level trigger laws on narrative strategies proved to be more multifaceted than initially hypothesized, revealing complex interactions with temporal factors that underscore the localized complexities of political communication. This section set the stage for a deeper discussion where these findings are interpreted in detail.

6. Discussion

The following discussion is structured to first interpret the key findings, exploring how different factors, such as partisanship and geographic variations, influence narrative strategies among U.S. representatives. This is followed by an investigation of the broader implications of these findings, particularly in relation to ethical considerations. I will also reflect on the methodological choices that shaped the research outcomes, discussing both the strengths and limitations of these approaches. Finally, the section will conclude with recommendations for future research.

6.1. Interpretation of Findings

The empirical analyses provide insights that contribute to both the fields of political communication and narrative policy analysis. In the following, I will discuss how representatives strategically utilize narratives of decline, diverging from expected celebratory rhetoric, to manage public perception and voter behavior in response to the overturning of *Roe v. Wade* and state-level trigger laws.

The analysis revealed a significant shift in the narratives of state representatives following the overturning of *Roe v. Wade*. The data indicated a clear move towards stories of decline in the aftermath of the Supreme Court's decision. The analyses further highlighted how important it is to examine narrative changes over time, particularly in response to significant political events. My results show that the representatives' use of decline narratives is not static but varies significantly around key dates related to *Roe v. Wade*. The substantial rise in decline narratives after the leak in May demonstrates that the representatives were likely leveraging a strategic communication approach to shape public opinion and political discourse in

anticipation of the Supreme Court's decision. This increase can be interpreted as a preemptive move to frame the potential overturning of *Roe v. Wade* in terms that would resonate with their constituents. Furthermore, the increase in decline narratives between the proposed 15-week abortion ban bill in September and the midterm elections in November is noteworthy. The timing of this narrative increase ahead of the midterm elections suggests a strategic use of messaging to potentially influence voting behavior. Politicians may leverage decline narratives to crystallize voter opinions on new legislative proposals, framing these policies as either threats or losses that must be responded to at the election. This can motivate voter turnout, particularly among those who feel most affected by the proposed changes.

Of note, the literature on the influence of Supreme Court decisions (Devins and Baum 2019; Roh and Haider-Markel 2003; Rohlinger 2006; Staggenborg 1988; Ziegler 2020) explains how such decisions can serve as catalysts that reshape the political landscape. These studies highlight the mobilization of political actors and the public, shifts in campaign themes, and changes in voting patterns in response to judicial rulings. My findings align with these insights by showing that the overturning of *Roe v. Wade* acted as a significant political and narrative catalyst. Additionally, my study showed that even the anticipation of the judicial decision in the form of leaked opinion draft had a strong effect on the representatives.

Contrary to the established view in academic literature (Carmines and Woods (2002), Carsey and Layman (2006), and Killian and Wilcox (2008)), which suggests a consistent alignment of partisan rhetoric with ideological positions, my study revealed a more differentiated approach by Republicans. The findings demonstrated that Republicans, rather than solely fortifying their traditional "pro-life" stance, strategically employed narratives of decline. This tactical choice diverges from the expected celebratory or affirmative narratives following a judicial victory that aligns with long-standing party goals. This approach is evident, particularly during the period surrounding the anticipated and actual overturning of *Roe v. Wade*. This divergence suggests a sophisticated use of abortion as a strategic tool, not merely to affirm ideological commitments but to manage potential backlash and align with broader, perhaps more moderate, segments of the constituents. This strategic narrative shift indicates an adaptive approach to influence fluctuating public opinion.

Therefore, while the literature has traditionally focused on how partisanship is expressed through consistent and predictable narrative frameworks, my study suggests that in the face of significant judicial changes, there can be strategic deviations from these established patterns. Republicans' use of decline narratives, particularly in a context where an ideological victory might otherwise call for celebratory framing, underscores a more calculated and responsive approach to political communication. This adaptation highlights a strategic depth that goes

beyond simple ideological expression, aiming to engage with a complex electorate during a politically volatile period.

Furthermore, my research highlights the impact of state-level trigger laws on political narratives and, therefore, how geographic and legislative contexts influence narrative strategies. My findings provide empirical evidence that representatives from states with active trigger laws may strategically adjust their narrative choices in anticipation of electoral implications, particularly the midterm elections. This strategic adaptation suggests a sophisticated level of narrative manipulation intended to influence voter behavior, supporting theories that understand political narratives as tools for electoral gain rather than mere reflections of ideological positions.

The significance of abortion as an electoral issue, as stated in the literature (Adams 1997; Cook, Jelen, and Wilcox 1992), is reflected in the narrative choices made by the representatives. According to Abramowitz (1995) and Sanbonmatsu (2002), many women consider a candidate's stance on abortion as a key factor in their voting choices, which underscores the potential electoral implications of how abortion narratives are framed. My results are in line with these previous findings, illustrating how the framing of abortion narratives can be crucial in influencing voter behavior and electoral outcomes. The use of decline narratives, particularly in a context that might rather call for triumphant rhetoric following a judicial win, suggests a more complex strategy of the representatives. This strategy considers the diverse opinions within the electorate on this issue and aims to position these representatives favorably ahead of forthcoming midterm elections.

6.2. Ethical Implications

From a practical standpoint, these findings draw several ethical considerations. Political actors play a crucial role in shaping public opinion and policy outcomes through their communication strategies. There is great ethical responsibility associated with this influence, especially in maintaining public trust and avoiding societal divisions. Elected representatives, in particular, have a moral obligation to use their platform for constructive discourse rather than divisive rhetoric.

The study's findings highlight the importance of critical media consumption. Individuals, media practitioners, and advocates must be aware that political narratives are often strategically crafted. Recognizing the underlying strategies in these narratives can help the public and analysts discern between genuine policy stances and strategic political positioning, leading to more informed discussions and decisions. Policy stances refer to the positions that representatives hold on specific issues based on their ideological beliefs and policy preferences. These stances are often communicated through narratives that reflect their genuine perspectives on policy matters. Strategic political positioning, on the other hand, involves the deliberate use of narratives to achieve specific political objectives, such as gaining

voter support, framing opponents, or shaping public discourse. While policy stances are rooted in ideological commitments, strategic positioning is more flexible and adaptive to the political context. An independent institution should monitor narrative practices in political campaigns and public discourse to educate the public on recognizing bias and evaluating political messages critically.

6.3. Strengths and Limitations

The study's strengths lie in its innovative use of machine learning to annotate and analyze large datasets. Supervised text classification has not been used in narrative policy analysis research to date. The integration of machine learning represents a significant advancement in the methodological approach to studying policy narratives. Furthermore, the research ensures a high level of data quality and reliability by carefully compiling a dataset and employing robust text classification methods. The application of the GLMM models allows for a detailed analysis of political narratives while accounting for individual variations. Another strength lies in the study's use of narrative policy analysis and its integration with political communication and framing theory. This theoretical grounding provides a solid framework for interpreting the narrative shifts observed in political discourse and offers valuable insights into how policy narratives evolve in response to judicial decisions.

Despite its strengths, this study is not without limitations that may impact the interpretation and generalizability of the findings. The study specifically selected tweets containing the keyword *abortion*. This approach excluded potentially relevant discussions that did not explicitly mention *abortion* but may have included related terms such as *Roe v. Wade*. Consequently, the dataset may not fully capture the entire spectrum of the public and political discourse surrounding the abortion law debate. The manual annotation of the subset of tweets introduces the risk of subjectivity, which could affect the classifier's predictions.

The supervised text classification, while effective, might be restricted by the selection of the polynomial kernel and the training data's potential biases. The SVM classifier with a polynomial kernel, although reasonably effective, has shown sensitivity to non-linear data separability. The choice of kernel and its parameters were selected based on the dataset at hand, which may limit the model's generalizability across more diverse or complex linguistic datasets not represented in the training data. Of note, there exists a potential for biases in the training dataset, which could influence the classifier's learning process. For instance, if certain narrative patterns are overrepresented in the manually annotated subset, the classifier may disproportionately favor these patterns when predicting new data.

Methodologically, while generalized linear mixed models account for individual variations and non-independence of observations, they may still be prone to unmeasured confounding factors. Media portrayal of abortion-related events and

fluctuations in public sentiment, as measured by opinion polls, may have shaped the content and tone of the representatives' tweets. Lastly, the study's findings are bound by the context of U.S. political discourse on abortion and may not be generalizable to other political issues or contexts. The specific nature of the abortion debate, deeply rooted in moral and ethical considerations, means that narrative strategies employed in this domain may differ from those in other policy areas.

Future research should continue to integrate and expand the use of machine learning techniques within policy process research. By experimenting with newer models and algorithms, scholars can enhance the precision and depth of classification of policy narratives. Additionally, incorporating sentiment analysis into the narrative policy analysis could provide deeper insights into the emotional tone and subjective underpinnings of narratives.

7. Conclusion

This study contributes to political science and narrative policy analysis by exploring how U.S. representatives use narrative strategies in the context of the landmark judicial decision overturning *Roe v. Wade*. The research demonstrated how political actors strategically adopt their policy narratives in response to this judicial change. The findings clearly showed a shift towards stories of decline following the Supreme Court's decision. This shift is not static but varies significantly around crucial dates, indicating a tactic use of narratives to influence public perception and political discourse preemptively. The increase in stories of decline—narratives that emphasize a worsening situation—was particularly pronounced before the midterm elections, suggesting a deliberate attempt to shape voter behavior in light of impending legislative changes.

The analysis also uncovered significant differences in how narratives are employed along partisan lines. Contrary to the traditional alignment of partisan rhetoric with ideological positions, Republicans displayed a complex use of decline narratives, indicating a strategic adaptation to broader, potentially more moderate voter bases. This finding suggests a departure from predictable partisan patterns and hints at a refined engagement with the constituents that goes beyond simple ideological claims.

Furthermore, the impact of state-level trigger laws revealed that geographical and legislative contexts significantly shape narrative strategies. Representatives from states with active trigger laws adjusted their narratives, reflecting the localized impacts of legal changes on their constituencies. This adaptation underscores the role of narratives as tools for electoral gain, strategically influencing to resonate with voter sentiments during crucial electoral periods.

The methodological approach of this study, integrating machine learning and generalized linear mixed models, provided a robust framework for analyzing the complexities of policy narratives. This approach not only ensured a high level of data

quality and reliability but also allowed for detailed analyses of how narratives evolve in response to political and judicial events. However, the study faced limitations such as potential biases from the selection of specific keywords and the manual annotation process, which might have influenced the classification outcomes.

Nevertheless, this research not only supports the application of narrative policy analysis in analyzing political discourse but also expands its use by exploring the impact of judicial decisions on narrative strategies. It stands as one of the first to apply narrative policy analysis in this context, offering new insights into how political narratives are crafted and deployed in the digital age.

Future research should further enhance the integration of machine learning in policy process research, exploring more sophisticated models and algorithms to improve narrative classification. Additionally, incorporating sentiment analysis could deepen understanding of the emotional dimensions of policy narratives.

In conclusion, this study offers important findings on the strategic use of political narratives, contributing significantly to theoretical and practical understanding of political communication in the context of major judicial changes. It highlights the dynamic interplay between legal decisions, electoral considerations, and narrative strategies while underscoring the powerful impact these elements have on democratic processes and public policy formulation.

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Appendix

Classifier Models' Performance Metrics			
Model	Accuracy	Recall	Precision
Boosted Trees (`C5.0`)	0.60	0.66	0.62
Decision Tree (`rpart`)	0.51	0.54	0.54
Logistic Regression (`glmnet`)	0.58	0.86	0.57
Logistic Regression (`LiblineaR`)	0.67	0.76	0.67
Logistic Regression (`stan`)	0.71	0.73	0.73
Multivariate Adaptive Regression Splines (`earth`)	0.67	0.73	0.68
Nearest Neighbor (`kkn`)	0.59	0.98	0.57
Random Forest (`ranger`)	0.65	0.73	0.65
SVM with Polynomial Kernel (`kernlab`)	0.71	0.76	0.71
SVM with Radial Basis Function (`kernlab`)	0.71	0.69	0.75

Table A1: Comparative Performance Metrics of Various Classifier Models. This table presents the accuracy, recall, and precision scores for each classifier model tested.

Bootstrap Analysis Results for Model 4

Bootstrap estimates including bias and standard errors.

Model Term	Original Estimate	Bias	Standard Error
Intercept	-0.212	-0.010	0.102
Party: Republican	-0.464	-0.060	0.163
Events: Between Leak and Overturning	0.312	0.016	0.124
Events: Between Overturning and Bill	0.139	0.000	0.109
Events: Between Bill and Elections	0.591	-0.002	0.126
Party * Events: R * Between Leak and Overturning	0.117	0.011	0.206
Party * Events: R * Between Overturning and Bill	0.738	0.071	0.228
Party * Events: R * Between Bill and Elections	0.723	0.078	0.209
Party * Events: R * After the Midterm Elections	-0.140	0.010	0.295
Events: After the Midterm Elections	0.250	-0.042	0.586

Table A2: Bootstrap Analysis Results for Model 4. The table presents the original coefficient estimates from the GLMM, along with the biases and standard errors obtained from 1,000 bootstrap replications. Key terms include the base intercept, affiliation to the Republican party, and various time events.

Bootstrap Analysis Results for Model 7			
Bootstrap estimates including bias and standard errors.			
Model Term	Original Estimate	Bias	Standard Error
Intercept	-0.301	-0.013	0.096
State Trigger Law	-0.308	-0.009	0.229
Events: Between Leak and Overturning	0.436	0.011	0.114
Events: Between Overturning and Bill	0.222	0.001	0.105
Events: Between Bill and Elections	0.653	-0.004	0.118
State Trigger Law * Events: 1 * Between Leak and Overturning	0.200	-0.011	0.202
State Trigger Law * Events: 1 * Between Overturning and Bill	0.033	-0.013	0.108
State Trigger Law * Events: 1 * Between Bill and Elections	0.522	0.020	0.259
State Trigger Law * Events: 1 * After the Midterm Elections	0.702	0.042	0.230
Party: Republican	-0.029	-0.023	0.302
State Trigger Law * Party: 1 * Republican	0.182	-0.007	0.552
Events: After the Midterm Elections	-0.160	-0.005	0.203

Table A3: Bootstrap Analysis Results for Model 7. The table presents the original coefficient estimates from the GLMM, along with the biases and standard errors obtained from 1,000 bootstrap replications. Key terms include the base intercept, state trigger laws, time events, and political party affiliation.

Overdispersion Check			
Results for Models 4 and 7			
Model	Residual Deviance	Degrees of Freedom	Overdispersion
Model 4	5,057.592	5,277	0.958
Model 7	5,060.577	5,275	0.959

Table A4: Overdispersion Check Results for Models 4 and 7. The table displays the results of overdispersion checks for Models 4 and 7. The residual deviance and degrees of freedom are reported for each model, along with the calculated overdispersion factor.

ANOVA Results Comparing Models with and without Random Effects for Model 4					
Term	Degrees of Freedom	Deviance	Residual Df	Residual Deviance	p-value (Pr > Chi)
	-	-	5287	7,329.744	-
party	1	2.025	5286	7,327.720	0.2
events	4	60.124	5282	7,267.596	2.73e-12
party:events	4	27.576	5278	7,240.019	1.52e-05

Table A5: ANOVA Results Comparing Models with and without Random Effects for Model 4. The table presents the results of an ANOVA comparing models with and without random effects for Model 4. The degrees of freedom, deviance, residual degrees of freedom, residual deviance, and associated p-values (Pr(>Chi)) are provided for each model term.

ANOVA Results Comparing Models with and without Random Effects for Model 7					
Term	Degrees of Freedom	Deviance	Residual Df	Residual Deviance	p-value (Pr > Chi)
	NA	NA	5287	7,329.744	-
state_trigger_law	1	0.794	5286	7,328.951	0.4
events	4	61.367	5282	7,267.583	0.00e+00
party	1	0.001	5281	7,267.582	1.0
state_trigger_law:events	4	18.572	5277	7,249.011	0.001
state_trigger_law:party	1	0.733	5276	7,248.277	0.4

Table A6: ANOVA Results Comparing Models with and without Random Effects for Model 7. The table presents the results of an ANOVA comparing models with and without random effects for Model 7. The degrees of freedom, deviance, residual degrees of freedom, residual deviance, and associated p-values (Pr(>Chi)) are provided for each model term.

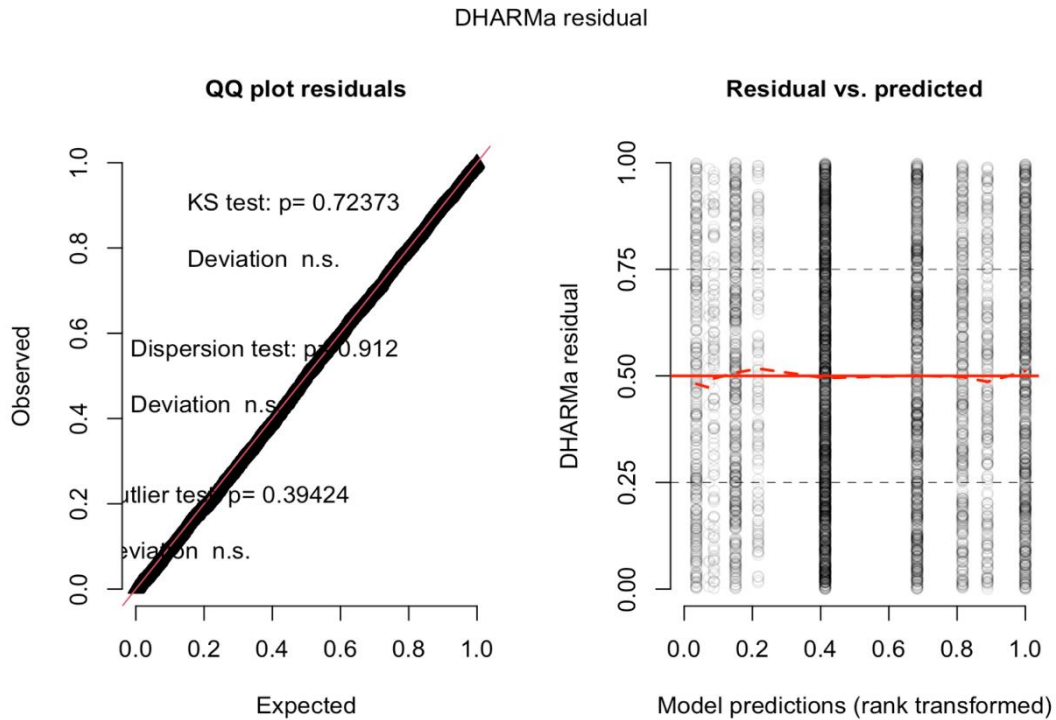


Figure A1: Residual Diagnostics using DHARMa for Model 4. The left panel displays a Quantile-Quantile (QQ) plot assessing the normality of residuals with Kolmogorov-Smirnov test results indicating no significant deviation from normality ($p=0.72373$). The right panel shows a scatter plot of residuals versus predicted values, illustrating the dispersion of residuals around the predicted outcomes with no apparent systematic patterns, as evidenced by non-significant dispersion and outlier test results.

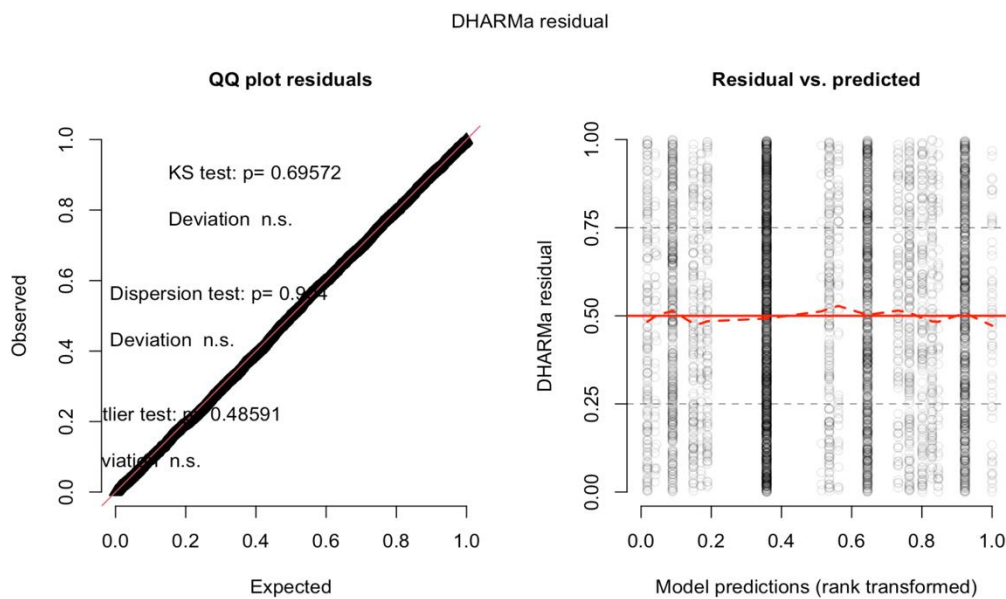


Figure A2: Residual Diagnostics using DHARMa for Model 7. The left panel displays a Quantile-Quantile (QQ) plot assessing the normality of residuals with Kolmogorov-Smirnov test results indicating no significant deviation from normality ($p=0.69572$).

The right panel shows a scatter plot of residuals versus predicted values, illustrating the dispersion of residuals around the predicted outcomes with no apparent systematic patterns, as evidenced by non-significant dispersion and outlier test results.