Silenced in the Chamber: Analyzing Gendered Speech Interruptions in the Australian Parliament (1998–2022)*

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First sentence. Second sentence. Third sentence. Fourth sentence.

1 Introduction

Interruptions are a defining feature of political discourse, often shaping the dynamics of power and influence within legislative bodies. While parliamentary rules in Australia officially prohibit interjections, disruptions remain a common occurrence, particularly in contentious debates where political tensions run high ("Interruptions to Members Speaking" 2025). Beyond their immediate impact on debate flow, interruptions may reflect deeper systemic biases, particularly in relation to gender. If women in Parliament are interrupted more frequently than their male colleagues, this pattern could signal broader inequalities in political representation and influence, warranting closer examination.

There has been considerable research on speech patterns and gender-based interruptions in government speeches across various countries. For instance, during U.S. Supreme Court confirmation hearings, female and minority nominees are interrupted more frequently than their male and white counterparts (Boyd, Collins, and Ringhand 2024). Additionally, in the US Congress, women also experienced more interruptions than men, especially during discussions of women's issues, where women are more than twice as likely to be interrupted compared to non-gendered topics (Miller and Sutherland 2022). In the Ecuadorian Congress, female legislators not only deliver fewer speeches but also speak for shorter durations compared to their male peers. Furthermore, women often wait longer to regain the floor after interruptions, leading them to strategically shorten their speeches to minimize further disruptions. However, women in authoritative positions can mitigate some of these interruption-related penalties, with senior

*Code and data are available at: https://github.com/hannahyu07/Hansard_Interruptions

women's speeches often exceeding those of men in length when they achieve comparable levels of experience or hold significant roles (Vera and Vidal 2021).

Contrastingly, studies of the Australian High Court reveal a different dynamic (Jacobi, Robinson, and Leslie n.d.). The result suggested that contrary to the U.S. Supreme Court, there is no significant difference between female and male justices regarding interruptions. Although women experience a higher rate of interruptions relative to their speaking time, the subtlety of this effect suggests that gender dynamics within the Australian court might be more balanced compared to the U.S. Supreme Court. This highlights the differences in how judicial interactions are influenced by gender across different legal systems.

Building on these findings, our study investigates gender-based interruptions in the Australian Parliament using the Australian Hansard, the official written record of parliamentary proceedings digitized by Lindsay Katz and Rohan Alexander (Lindsay Katz and Alexander 2023). We first analyze the frequency and patterns of interruptions directed at male and female parliamentarians to assess whether gender influences how often speakers are interrupted. Beyond interruptions, we extend our analysis by examining the topics discussed in Parliament each year using Structural Topic Modeling (STM). This allows us to explore whether certain policy areas are associated with higher interruption rates and whether women engage in different policy discussions than men. By connecting these two aspects, we aim to identify whether interruptions are more prevalent in specific years and whether they coincide with particular topics, shedding light on how gender and discourse shape parliamentary debate.

The remainder of this paper is structured as follows: Section 2 demonstrates the data used for this paper, Section 3 describes, justifies, and explains my model, Section 4 highlights the results of the predictions using tables and graphs, and Section 5 contains important implications and conclusions based on the findings.

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library(tinytex)
```

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Warning: package 'tinytex' was built under R version 4.3.3
```

```
#install.packages("tinytex")
#tinytex::install_tinytex()



#tinytex::tlmgr_update()
#tinytex::tlmgr_install("latex-bin")
#tinytex::tlmgr_install("xetex")

#.libPaths()  # Check all library paths
#find.package("rlang")  # Identify where the old version is installed
```

xelatex –version

2 Data

Data analysis is performed using statistical programming language R (R Core Team 2023), with packages `tidyverse` (Wickham et al. 2019), `arrow` (Richardson et al. 2024), `here` (Müller 2020), `rstanarm` (Goodrich et al. 2022), `modelsummary` (Arel-Bundock 2022), `ggplot2` (Wickham 2016), `knitr` (Xie 2014), `tibble` (Müller and Wickham 2023), `gt` (Iannone et al. 2024), `patchwork` (Pedersen 2024), `testthat` (Wickham 2011), `kableExtra` (Zhu 2021), `dyplyr` (Wickham et al. 2023), `stringr` (Wickham 2023), and `lubridate` (Grolemund and Wickham 2011).

2.1 Data Source

The data used in this research is a compiled digital record of the Australian Hansard that documents parliamentary proceedings from 1998 t0 2022 (L. Katz and Alexander 2022). This comprehensive database includes variables such as speaker details (e.g., name, party, gender, electorate), timestamps, speech content, and flags for interjections, questions, and other procedural elements. This dataset is favoured for its utility in examining parliamentary gender dynamics, speech patterns, and the evolution of political discourse over an extensive period.

2.2 Data Cleaning

To ensure consistency and accuracy in the analysis, we performed several data cleaning steps on the Hansard corpus dataset. One of the primary tasks was standardizing categorical variables, correcting data types, and filtering the dataset to focus on relevant parliamentary debates.

First, we standardized the gender variable by converting it to a character type and addressing missing values. Any NA or empty string entries were replaced with "Unknown", ensuring that all observations were categorized as "Male", "Female", or "Unknown". Next, we processed the interjection (interject) variable, which indicates whether a speech was interrupted. Since it was originally stored as a mix of character and numeric values, we converted it into a numeric format while preserving any missing values. Similarly, the date column was transformed into a proper Date format (YYYY-MM-DD), and we extracted the year variable for longitudinal analysis.

A critical filtering step was applied to retain only chamber speeches (fedchamb_flag == 0). This decision was made because chamber debates represent formal parliamentary discussions, including legislative debates and question periods, where interruptions carry significant political and procedural weight. In contrast, committee hearings and other non-chamber sessions

often have different procedural norms and may not exhibit the same interruption patterns. Focusing on chamber data ensures that our findings reflect structured parliamentary interactions rather than informal or committee-based discussions.

Additionally, we computed the word count for each speech by applying a regular expression that counts the number of words in the speech text (body). This provides insights into the length of speeches, which may be relevant in later analyses.

(**preview_cleaned?**) provides a snapshot of key variables, including year, gender, interject, party, and word_count, allowing us to inspect how the dataset is structured post-cleaning. (**sum_stats?**) presents aggregated counts of speeches by gender, interruption status, and party affiliation. It highlights the number of speeches given by male and female parliamentarians, how often interruptions occur, and the distribution of party representation. Missing values are explicitly recorded where relevant.

Table 1: Preview of the Cleaned Hansard Dataset

year	gender	interject	party	word_count	fedchamb_flag
1998	Unknown	0	NA	18	0
1998	Unknown	0	NA	18	0
1998	Female	0	LP	771	0
1998	Male	0	ALP	919	0
1998	Male	0	LP	1377	0
1998	Unknown	0	NA	31	0

Table 2: Summary Statistics of the Cleaned Hansard Dataset

Variable	Category	Count
Gender	Male	292267
Gender	Female	65022
Gender	Unknown	148705
Interject	No	411001
Interject	Yes	94993
Party	ALP	155066
Party	LP	144258
Party	Nats	10336
Party	Other	31331
Party	Missing	165003

By ensuring data consistency and filtering for relevant parliamentary discourse, these preprocessing steps provide a clean and structured dataset, ready for further analysis on gender-based interruptions and topic modeling in Australian parliamentary debates.

2.3 Measurement

The Hansard dataset represents various real-world parliamentary phenomena through carefully constructed variables. However, as with all datasets, some considerations and limitations arise when transitioning from real-world events to structured data. This section discusses what the variables of interest are measuring and potential challenges in their representation.

Firstly, the variable interject, which indicates whether a speaker's statement was interrupted, relies on the identification of interruptions as recorded in the Hansard transcripts. However, the variable may not fully capture the intent or context of interruptions, as it cannot distinguish between interruptions made in jest, as points of order, or as serious challenges. Additionally, subtle interruptions not formally acknowledged in the record or overlapping statements may go unflagged.

The variable gender, representing the speaker's gender, was inferred by merging the dataset with external biographical sources, such as the AustralianPoliticians package. While this approach ensures consistency, it assumes the accuracy of external data sources, which may contain errors or outdated information. Furthermore, the binary classification of gender in the dataset does not account for non-binary or other gender identities, potentially limiting the scope of gender-based analyses.

The party variable categorizes speakers by their political affiliation. This information is directly parsed from the Hansard transcripts, where the party name or abbreviation is provided alongside the speaker's details. However, variations in party naming conventions, particularly for smaller or region-specific parties, required standardization using external datasets like Party Facts. These efforts may introduce minor inconsistencies, especially in cases of historical party name changes or mergers.

Lastly, word_count quantifies the length of each speech by counting the number of words in the speech text. While straightforward to compute, this variable does not differentiate between substantive contributions and procedural or repetitive language. Additionally, transcription errors or inconsistencies in the Hansard record might slightly affect word count accuracy, though these are rare.

Overall, while the variables provide meaningful representations of parliamentary behavior, they are shaped by the limitations of transcription accuracy, data inference, and structural simplifications inherent in processing complex real-world phenomena.

2.4 Outcome Variables

The outcome variable, interject, serves as a binary indicator of whether a speaker was interrupted during their speech. To explore the distributions of interruptions over years, we introduce the following plots. Figure 1 illustrates interruptions in the Australian Parliament from 1998 to 2022, categorized by gender. Notably, male speakers consistently faced more

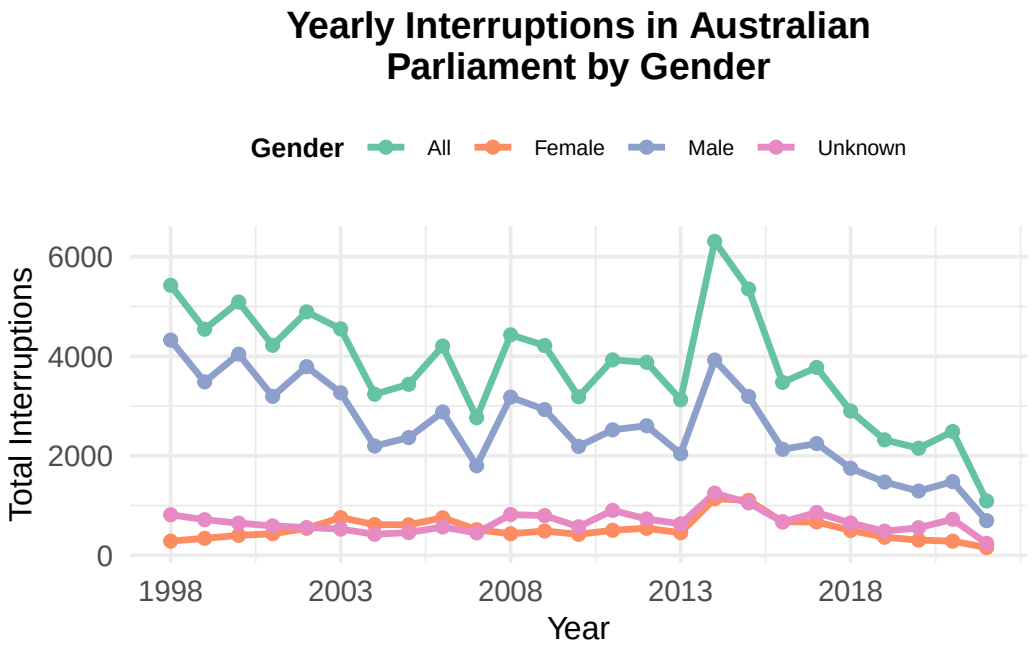

Figure 1: Yearly Interruptions in Australian Parliament by Gender

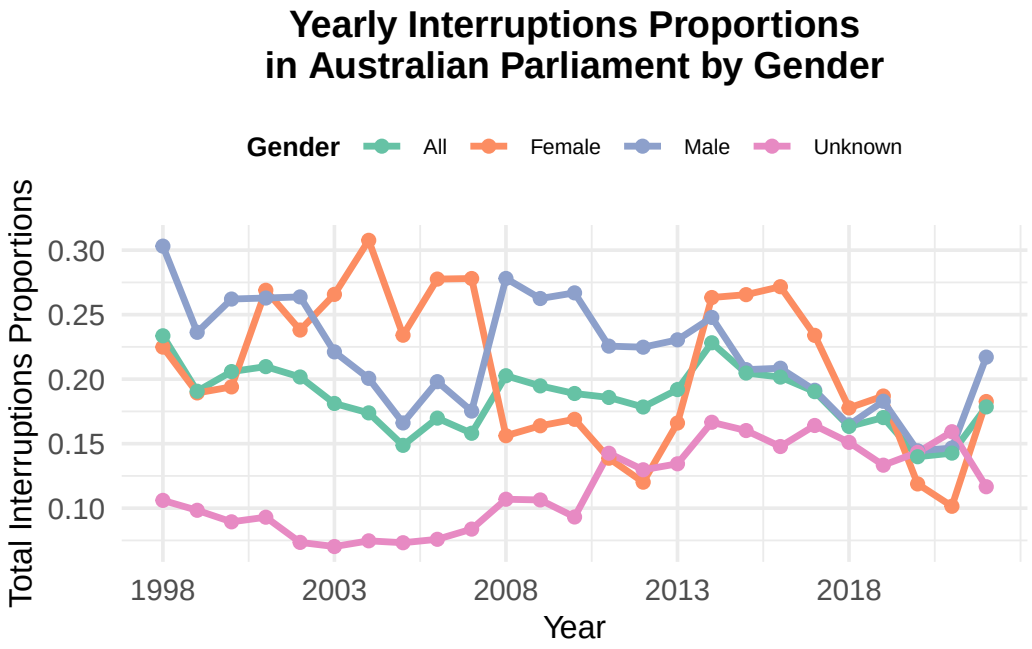

Figure 2: Yearly Interruptions Proportions in Australian Parliament by Gender

Table 3: Gender-Based Interruption Analysis in Parliamentary Speeches

Proportion of Interruptions by Gender

Gender	Total Interruptions	Total Speeches	Interruption Proportion
Female	13301	65022	20.00%
Male	64995	292267	22.00%
Unknown	16697	148705	11.00%
All	94993	505994	19.00%

interruptions than females, with a peak in 2011 and a subsequent decline. Female speakers experienced fewer interruptions, with relatively stable figures across the years. The "Unknown" category, consistently low, suggests either minimal occurrence or documentation of such interruptions.

To provide a fair comparison of interruptions across different genders within the Australian Parliament, we normalize the data by calculating proportions. This method addresses the gender imbalance in parliament, ensuring that the analysis reflects the frequency of interruptions relative to each gender's representation. Figure 2 presents the proportions of speeches interrupted by gender. It indicates that male speakers had a higher proportion of their speeches interrupted, especially during the mid-2000s to early 2010s, though the gap between genders has narrowed over time. The proportion of interruptions for female speakers generally mirrors these fluctuations, implying that specific topics or periods may have incited more active parliamentary interactions. The "Unknown" gender shows minimal changes, highlighting its limited data representation. This analysis points out both the consistency and evolution of gender dynamics within parliamentary debates over the years.

2.5 Predictor Variables

The predictor variables in this analysis capture key characteristics and contextual factors that may influence the likelihood of interruptions during parliamentary speeches. Gender represents the speaker's gender, allowing us to examine whether men and women experience interruptions at different rates. Party indicates the speaker's political affiliation, reflecting potential partisan dynamics that could impact speech interactions. The government status variable identifies whether the speaker belongs to the governing party, which may affect their level of authority or the degree of scrutiny they face from the opposition. Lastly, the word count quantifies the length of each speech, providing insight into whether longer speeches are more likely to invite interruptions. Together, these variables offer a comprehensive framework for understanding how personal and contextual factors contribute to the dynamics of parliamentary discourse.

Table 3 provides a clear view of the proportion of interruptions by gender across all speeches in the dataset. The results show that male speakers were interrupted more frequently (21%

of speeches) compared to female speakers (18% of speeches). Interestingly, the interruption proportion for unknown gender speakers is significantly lower, at only 11%. Overall, considering all speeches regardless of gender, the interruption proportion stands at 18%. This data suggests that gender may play a role in how frequently speakers are interrupted during parliamentary sessions, with male speakers facing a higher rate of interruption. This could reflect broader dynamics of gender interaction within the parliamentary setting.

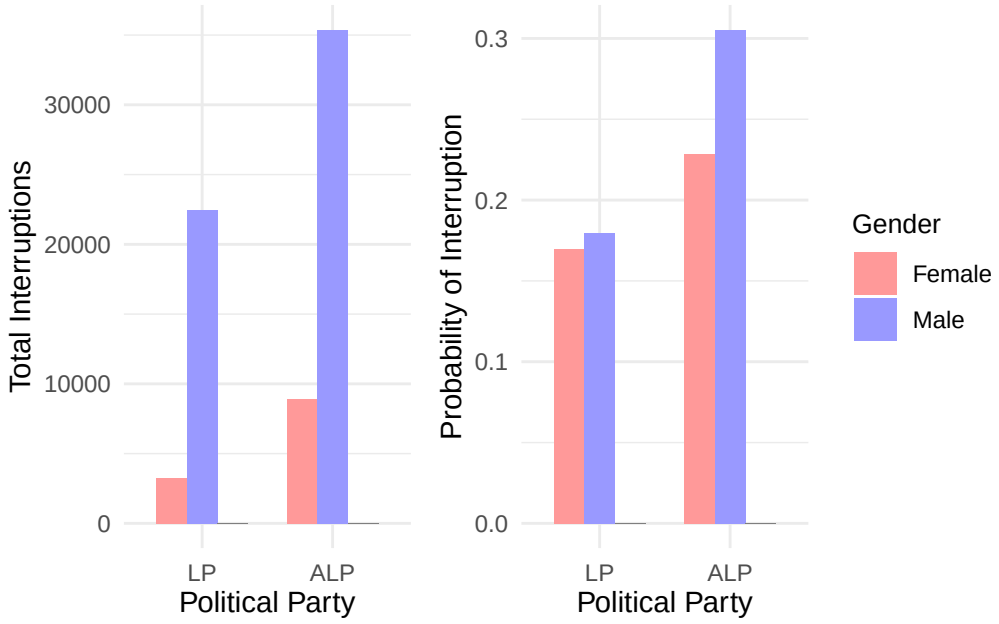

Figure 3: Interruptions in Major Australian Political Parties by Gender

Figure 3 focuses on the Liberal Party (LP) and the Australian Labor Party (ALP), the two major parties in Australian politics, to analyze interruptions by gender. Since these parties dominate parliamentary proceedings, they provide a significant sample of gender interaction dynamics. The total interruptions are higher in the ALP compared to the LP, with male members experiencing more interruptions than female members in both parties. We use proportions to normalize the data, accounting for differences in gender representation within these parties. This approach helps us understand the rate at which female and male members are interrupted relative to their participation, offering a clearer insight into the parliamentary discourse dynamics.

Table 4 and Figure 4 offer a detailed look at interruptions during parliamentary sessions, categorized by members' government status and gender. Notably, interruptions are extremely rare for members with clearly identified status. This indicates a potential correlation between established government status and more orderly interactions, highlighting the importance of role clarity in maintaining decorum.

Table 4: Interruption Summary by Government Status

Government Status	Interruption	Count
In Opposition	Yes	4
In Opposition	No	42920
In Government	Yes	22
In Government	No	61244
NA	Yes	94967
NA	No	306837

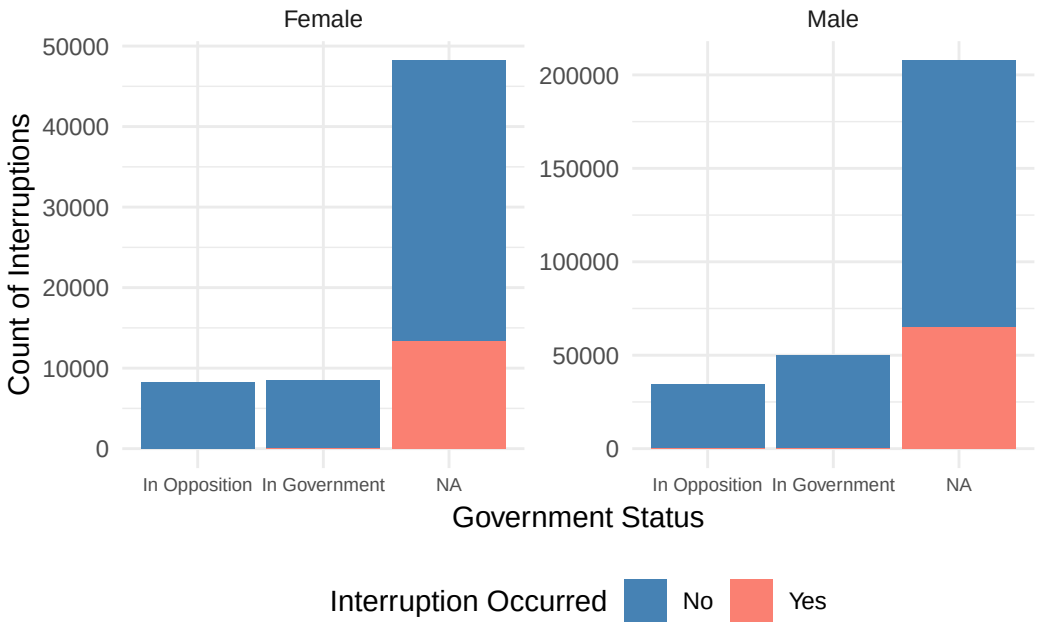

Figure 4: Count of Interruptions by Government Status and Gender

However, the significant amount of missing data makes reliable inferences about the true nature of interruptions and their correlation with member status challenging. The vast majority of interruptions occur when the government status of the speaker is unknown. This trend is consistent across both the comprehensive dataset and the subset limited to non-federal chamber sessions. Interruptions are exceedingly rare for members whose government status is known, with only 22 interruptions for those "In Government" and an even fewer 4 for those "In Opposition" across all data. Due to this substantial amount of missing information, it is very difficult to firmly conclude whether our observed patterns hold true.

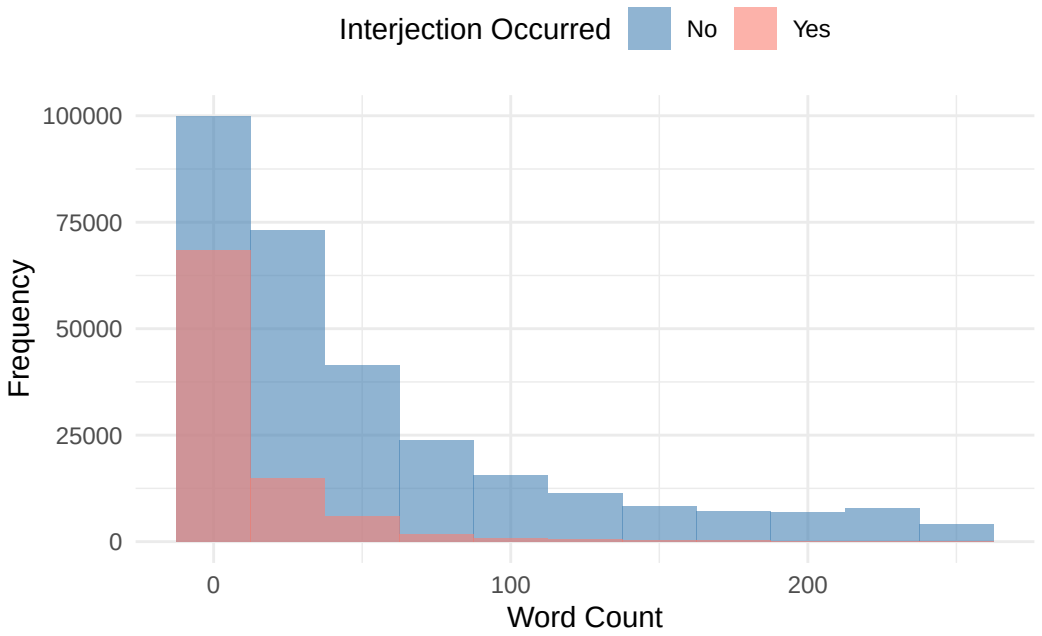

Figure 5: Histogram of Word Counts in Speeches (Up to 250 Words)

Figure 5 shows word counts in speeches divided into two categories: speeches where an interjection occurred and those without any interruptions. We can see that speeches without interruptions (blue bars) are more frequent across all word count ranges, especially as the number of words increases. Conversely, interrupted speeches (red bars) are less frequent and generally shorter. This trend suggests that interruptions tend to happen in shorter speeches or possibly cause speakers to shorten their remarks. This graph gives a clear visual indication of how interruptions might disrupt or influence the length of parliamentary speeches.

The density plot Figure 6 shows that the word count distribution for both male and female speakers is highly left-skewed, with the majority of speeches being very short. Both genders peak at shorter speeches, but male speakers tend to have even shorter speeches compared to females, as indicated by the higher peak density for men in the lower word count range. Notably, female speakers show a small rise in density between word counts of 200 and 300, suggesting

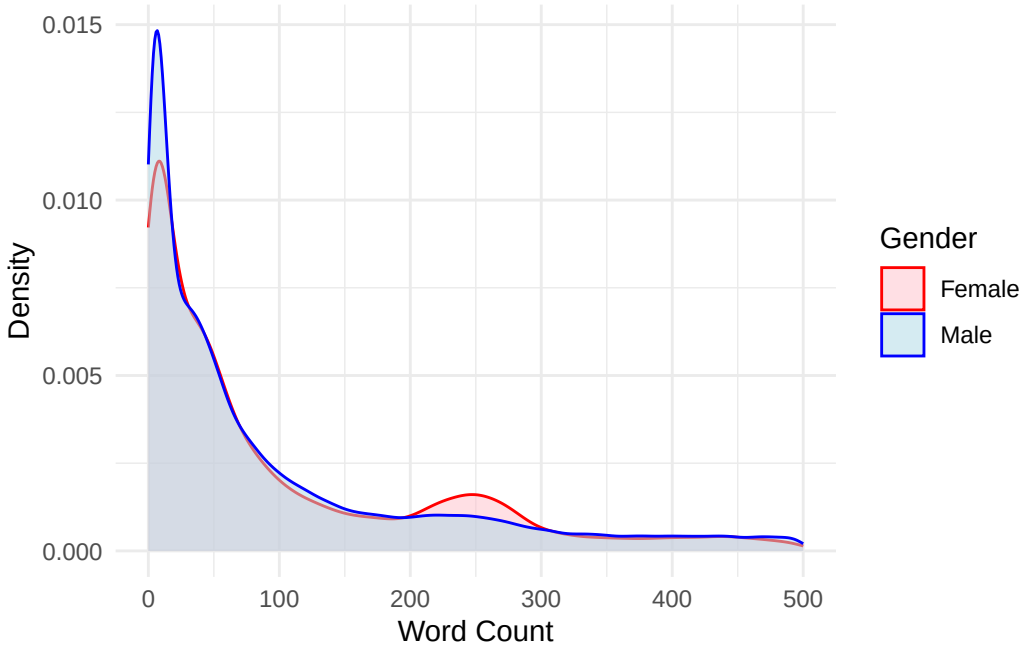

Figure 6: Density Distribution of Word Count by Gender (Word Count < 500)

Table 5: Gender-Based Interruptions and Word Count

Gender	Interruption	Total Speeches	Average Words	Min Words	Max Words
Female	0	51721	519.30648	1	28893
Female	1	13301	35.78806	1	12762
Male	0	227272	410.61115	0	55752
Male	1	64995	28.39659	1	26098

that a subset of their speeches tends to be slightly longer compared to their male counterparts. This subtle difference highlights variation in speaking patterns between genders.

Table 5 highlights that, on average, females tend to speak longer than males before an interruption occurs. For uninterrupted speeches, females average 560.72 words compared to 448.67 words for males. Even when interrupted, female speeches still have a higher average word count (37.76 words) than interrupted male speeches (28.76 words). This suggests that while females may face greater challenges overall, they tend to hold the floor longer before interruptions occur. However, the substantial drop in average word count for both genders during interruptions shows the disruptive impact, with females experiencing a steeper decline relative to their uninterrupted averages. This pattern indicates that while females often manage to speak at greater length initially, interruptions disproportionately diminish their overall

speaking opportunities.

3 Model

3.1 Model set-up

I utilized a Bayesian logistic regression model to examine the relationship between speech interruptions and the speakers' genders. The model is formulated as follows:

$$
\begin{aligned}
y_i|\pi_i &\sim \text{Bern}(\pi_i) \qquad (1)\\
\text{logit}(\pi_i) &= \alpha + \beta_1 \times \text{gender}_i + \beta_2 \times \text{party}_i + \beta_3 \times \text{word\_count}_i + \beta_4 \times \text{word\_count\_gender}_i\\
\alpha &\sim \text{Normal}(0, 5)\\
\beta_1 &\sim \text{Normal}(0, 2.5)\\
\beta_2 &\sim \text{Normal}(0, 2.5)\\
\beta_3 &\sim \text{Normal}(0, 2.5)\\
\beta_4 &\sim \text{Normal}(0, 2.5)
\end{aligned}
$$

In this model, (y_i) represents the binary outcome variable indicating whether a speech was interrupted ((interject = 1)) or not ((interject = 0)). The probability of an interruption ((_i)) is modeled using a logistic link function, where the log-odds of an interruption are expressed as a linear combination of the intercept (( )) and the predictor variables: where (_1, _2, _3, _4) are the regression coefficients corresponding to each predictor. The variables included in the model are defined as follows: (gender_i) represents the speaker's gender (Male, Female, or Unknown), (party_i) indicates the political party affiliation, (word_count_i) captures the total number of words spoken in a given speech, and (word_count_gender_i) represents the interaction between word count and gender.

To regularize the model and incorporate prior information, we assign informative normal priors to the intercept and coefficients. Specifically, the intercept ( ) follows a normal distribution with a mean of 0 and a standard deviation of 5, while the coefficients (_1, _2, _3,) and (_4) follow normal distributions with a mean of 0 and a standard deviation of 2.5. These priors help stabilize the estimates, particularly in cases where the data might be sparse or imbalanced.

This modeling approach is chosen for several reasons. Firstly, logistic regression is well-suited for binary outcome variables, making it appropriate for interruption probabilities. Additionally, Bayesian logistic regression is particularly well-suited for this analysis because it accommodates uncertainty in parameter estimates and allows for the incorporation of prior knowledge. Bayesian methods are advantageous in addressing potential multicollinearity and producing interpretable probabilistic estimates.

The model was implemented in R using the `rstanarm` package (Goodrich et al. 2022), which applies Markov chain Monte Carlo (MCMC) sampling to estimate the posterior distributions of the model parameters. To optimize computational efficiency, I randomly sampled 1000 observations for model fitting, ensuring a balance between computational feasibility and statistical reliability.

4 Results

Table 6 identifies key predictors including gender, party, and word count of speech interruptions in parliamentary proceedings. Gender plays an important role, with male speakers more likely to experience interruptions compared to female speakers. This suggests that men face slightly higher odds of interjections during their speeches. Party affiliation also significantly influences interruptions, with some parties, such as the ALP, experiencing more frequent interjections, while others, like the LNP, are interrupted less often. These patterns highlight how political dynamics can shape interactions in debates.

Additionally, the length of speeches affects interruptions, with longer speeches slightly less likely to be interrupted, suggesting that concise speeches may invite more interjections. Notably, the interaction between word count and gender reveals that male speakers experience a slight increase in interruptions as their speech length increases, a trend that is less pronounced for female speakers. These findings underscore the combined effects of gender, party dynamics, and speech characteristics in shaping interruption patterns.

Model diagnostics, including convergence checks and posterior summaries, and explanations can be found in (**Appendix?**)

The Bayesian logistic regression model quantifies gender-based interruptions in the Australian Parliament, assessing whether female speakers face disproportionately more interjections than their male counterparts. However, interruptions alone do not fully capture discourse dynamics. To further explore these patterns, I applied Structural Topic Modeling (STM) to identify the most discussed topics in parliamentary speeches, incorporating gender and party affiliation as prevalence covariates to examine how different groups engage with various topics.

By linking the most discussed topics in a given year to the most interrupted gender, I aim to determine whether interruptions are associated with particular types of discourse. For example, if female parliamentarians experienced the highest interruption rates in 2020, I will compare this with the dominant topics that year to uncover potential gendered patterns. This dual approach—quantifying interruptions through regression and analyzing speech content through topic modeling—offers deeper insight into both who gets interrupted and what is being discussed when those interruptions occur.

The process began with data preprocessing, where I filtered the dataset to include only relevant entries, removed missing values, and structured the text data for analysis. A document-feature matrix (DFM) was then created, representing word frequencies while eliminating punctuation,

Table 6: Model 1 for Interruptions (n = 1000)

	Speech Interrupted
(Intercept)	−0.723
	(0.266)
genderMale	0.409
	(0.268)
genderUnknown	−0.854
	(2.059)
partyALP	0.638
	(0.186)
partyIND	−0.060
	(0.745)
partyNP	0.017
	(0.601)
partyCLP	0.317
	(1.253)
partyInd	1.817
	(0.961)
partyNPA	1.998
	(1.382)
partyLIB	1.022
	(1.094)
partyNATS	−0.756
	(1.100)
partyAG	−1.751
	(1.722)
partyInd.	0.831
	(1.297)
partyNats	−0.510
	(0.683)
partyAUS	−0.052
	(2.418)
partyCA	−0.533
	(2.063)
partyKAP	−1.396
	(1.813)
partyLNP	−1.559
	(0.962)
word_count	−0.015
	(0.002)
word_count_gender	0.008
	(0.003)
Num.Obs.	1000
R2	0.250
Log.Lik.	−382.527
ELPD	−408.4
ELPD s.e.	35.0
LOOIC	816.8
LOOIC s.e.	70.0
WAIC	813.1
RMSE	0.34

stopwords, and low-frequency terms to improve model efficiency. The STM model was trained with 10 topics and incorporated party affiliation and speaker gender as prevalence covariates, allowing for an examination of how these factors influence topic distribution. The model was optimized over 50 iterations, ensuring convergence and stability. The final output provided a breakdown of the dominant topics, with key terms extracted using highest probability words, FREX words (distinctive to each topic), Lift words (rare but highly relevant), and Score words (best summarizing a topic's meaning).

To analyze the evolution of parliamentary discourse over time, I ran the Structural Topic Model (STM) on each year from 1998 to 2022, extracting the most prominent topics discussed in Australian parliamentary speeches annually. This approach allows us to track changes in political priorities and public policy discussions across different governments and time periods.

Table 7 that extracted topics from Australian parliamentary speeches from 1998 to 2022 reveal recurring themes in economic policy, governance, and public welfare. In 1998, keywords such as "funding, economy, billion, jobs, growth" indicate a strong focus on financial matters, possibly reflecting the economic policies of the Howard government. By 1999, discussions shifted toward legislative processes, with terms like "committee, country, parliament, act, bill, interest", suggesting an emphasis on governance and parliamentary procedures.

In the early 2000s, taxation and economic regulation became central themes. The year 2000 prominently features "tax, GST, regional, cost", likely indicating debates around the introduction of the Goods and Services Tax (GST), a major economic reform at the time. By 2001, discussions expanded to include "question, education, state, leader, speaker", showing parliamentary focus on education policy and leadership discussions. The presence of "security, report, speaker" in later years, such as 2007, suggests increasing discussions about national security and legislative oversight.

The financial crisis of 2008 appears to have influenced parliamentary discussions, as evidenced by the prominence of "government, economic, parliament, working" in that year. This aligns with government efforts to stabilize the economy and implement stimulus measures. By 2010, speeches featured "policy, education, billion, services", indicating continued investment in education and public services. In 2015, "education, students, infrastructure, training, funding" suggests an ongoing emphasis on higher education and workforce development.

More recently, parliamentary discussions reflected the impact of the COVID-19 pandemic. In 2020, "government, security, legislation, parliament" emerged as dominant themes, which likely relate to emergency public health measures and pandemic response policies. By 2021 and 2022, terms such as "community, health, local, member" indicate a growing focus on public health, social support, and government intervention in economic recovery.

Overall, this analysis provides a clear trajectory of parliamentary priorities over time. While early discussions centered on economic policy and legislative procedures, later years saw a growing emphasis on education, national security, and, more recently, public health. The keywords extracted from parliamentary speeches highlight shifting political and policy concerns, aligning with major national and global events during this period.

Table 7: Most Prominent Topics Per Year

Most Prominent Topics Per Year

Year	Representative Keywords
1998	$, funding, australia, economic, billion, jobs, million, economy, growth, program
1999	committee, may, country, community, parliament, act, can, see, bill, interest
2000	tax, mr, time, said, gst, regional, need, people, country, cost
2001	question, last, say, can, prime, state, make, education, leader, speaker
2002	new, australia, commonwealth, education, order, made, time, particular, opportunity, development
2003	make, place, issue, fact, report, parliament, medicare, may, policy, order
2004	also, last, now, ‘, speaker, new, money, free, local, today
2005	now, go, today, small, member, want, know, see, interest, economy
2006	australia, minister, member, new, question, debate, point, electorate, howard, world
2007	mr, prime, question, water, act, committee, australia, security, report, speaker
2008	government, now, prime, economic, families, cent, see, parliament, working, say
2009	$, member, now, said, opposition, million, think, students, make, future
2010	will, government, $, national, question, services, million, policy, education, billion
2011	government, minister, tax, prime, question, policy, say, economy, cost, economic
2012	member, support, year, say, make, today, work, great, future, local
2013	people, tax, health, education, per, business, first, scheme, government’s, private
2014	will, make, get, need, us, say, country, question, business, system
2015	education, students, infrastructure, training, higher, university, project, energy, sector, funding
2016	time, per, need, can, want, well, think, budget, system, see
2017	$, budget, health, services, billion, million, government’s, care, can, disability
2018	bill, will, australian, minister, committee, legislation, report, also, family, law
2019	prime, also, question, funding, future, house, home, now, care, standing
2020	ensure, national, australian, security, support, legislation, measures, government, parliament, informatic
2021	member, community, health, world, future, make, look, children, take, nation
2022	minister, community, prime, thank, also, see, member, local, health, take

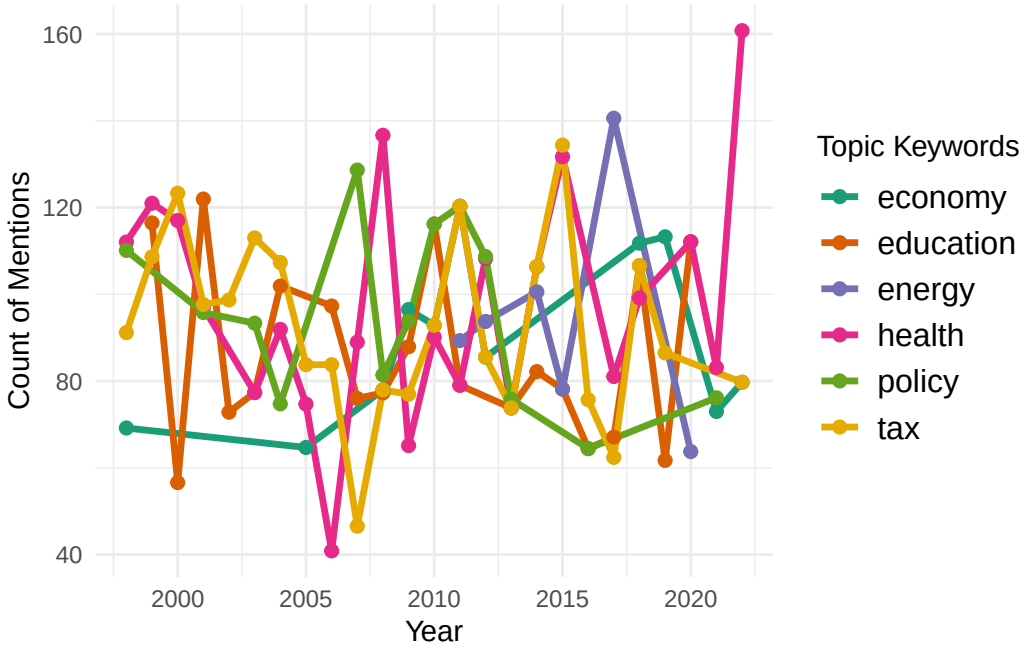

Figure 7: Mentions of Key Topics Over Time

Figure 7 tracks the mentions of key policy topics—economy, education, energy, health, policy, and tax—in Australian parliamentary speeches from 1998 to 2022. Each topic fluctuates over time, reflecting shifts in legislative focus due to major events.

Economic discussions remain stable but rise post-2008, aligning with the global financial crisis. Tax mentions spike around 2000, likely due to the introduction of the GST, and reappear during key economic reforms. Health surges in 2020, reflecting COVID-19 discussions, while education remains consistently relevant, peaking during policy changes in higher education and funding. Energy mentions rise after 2010, coinciding with climate policy debates like the carbon tax (2012-2014). The steady increase in policy discussions suggests a growing focus on governance and regulatory matters. These trends highlight how parliamentary attention shifts in response to national and global developments such as economic crises, education reforms, climate policies, and the pandemic.

Table 8 displays the more interrupted gender every year in the parliament and compares all members and only chamber members. While most years are the same, there is a notable shift in the gender experiencing more frequent interruptions from 2018 to 2020. In the broader dataset, males were more frequently interrupted; however, this pattern shifts in the non-federal chamber data, where females became the more interrupted gender during these years. This change highlights the variability in gender dynamics within different parliamentary environments and suggests that factors specific to non-federal chamber settings may influence these interaction patterns more significantly for female members.

Table 8: Gender Interruption Proportions Annual Comparison

Year	More Interrupted Gender
1998	Male
1999	Male
2000	Male
2001	Female
2002	Male
2003	Female
2004	Female
2005	Female
2006	Female
2007	Female
2008	Male
2009	Male
2010	Male
2011	Male
2012	Male
2013	Male
2014	Female
2015	Female
2016	Female
2017	Female
2018	Female
2019	Female
2020	Male
2021	Male
2022	Male

The relationship between key discussion topics and gender-based interruptions in the Australian Parliament reveals interesting patterns over time. One notable observation is that years with significant shifts in dominant topics often correspond to changes in the most interrupted gender. For example, in 2001 and 2003–2007, when female parliamentarians faced more interruptions, discussions around education, policy, and health were prominent. This suggests that women may have been more vocal in policy-driven debates during these years, potentially contributing to higher interruption rates. Conversely, in years when male speakers were interrupted more often, such as 1998–2000, 2008–2013, and 2020–2022, the most discussed topics included economy, tax, and government policy, indicating that male parliamentarians may have taken the lead in these areas.

Another striking trend is the spike in health-related discussions in 2020, which coincides with a shift back to male parliamentarians being more interrupted. This could reflect the heightened focus on COVID-19-related policies, with male politicians engaging in more contentious discussions. Similarly, 2018 and 2019 saw female parliamentarians experiencing the highest interruptions, aligning with rising debates on legislation and social policies—areas where women may have had greater involvement.

Overall, these findings suggest that interruption patterns are not random but are influenced by the topics dominating parliamentary discourse each year. When discussions center on traditionally social or policy-oriented issues, women appear to face higher interruption rates, while economic and government-related debates tend to correspond with increased interruptions for male speakers. This interplay between gender, parliamentary discourse, and interruptions underscores how power dynamics in political speech are shaped by both who is speaking and what is being discussed.

4.0.1 Model justification

We expect a positive relationship between the= size of the wings and time spent aloft. In particular...

We can use maths by including latex between dollar signs, for instance θ.

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

Please don't use these as sub-heading labels - change them to be what your point actually is.

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

```
library(bayesplot)
```

```
This is bayesplot version 1.11.0

- Online documentation and vignettes at mc-stan.org/bayesplot

- bayesplot theme set to bayesplot::theme_default()

   * Does _not_ affect other ggplot2 plots

   * See ?bayesplot_theme_set for details on theme setting
```

```
#mcmc_trace(as.array(model1))
```

```
#pp_check(model1, nsamples = 100)
```

A Additional data details

B Model details

B.1 Posterior predictive check

B.2 Diagnostics

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