Language of War: Linguistic Differences in Political Discourse Involving Conflict

*Keywords:* psycholinguistics, war, discourse, word frequencies

**Abstract**

Choosing to start a war carries with it great consequences; therefore, it is of utmost importance to understand what predicts support for war. We examined how word use predicted support for military action in the U.S. Congress. Previous research has tied political language to legislative success, party differences, and war, while others have examined the role of the executive and public support for war. However, the role of the legislative in war has been understudied. The present study hypothesized that word frequencies of function and content words would predict support for military action in the U.S. Congress. From the Congressional Record, speeches were obtained pertaining to the decisions for the U.S. to take military action in Kosovo, Iraq, and Libya. Using multilevel logistic regression, we found the use of singular third person pronouns to strongly predict support for war among both senators and representatives. Other significant predictors such as money, death, and social concepts were found for representatives but not senators.

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In the last few years, numerous civil disputes worldwide, which might threaten American interests and human rights, have spurred considerable debate over American military intervention. In fact, throughout history, nations were periodically faced with choices about a declaration of war. Over the past two decades, the U.S. and its allies have faced a variety of international threats and difficulties including possible nuclear weapons, hostile/unfriendly nations such as Iran, and human rights abuses and genocide in Sudan and other nations. Despite declines in legislative control of foreign policy, the U.S. Congress still plays an important role in deciding how the military is used by retaining the rights to formally declare war, limit the use of military force, and control military appropriations (Phelps & Boylan, 2002). Previous research examined the predictors of presidential use of military force (Clark & Nordstrom, 2005; Keller & Foster, 2012) and predictors of public support for war (Cohrs & Moschner, 2002; Friese, Fishman, Beatson, Sauerwein, & Rip, 2009; McCleary, Nalls, & Williams, 2009). However, the predictors of legislative support of military action have been understudied, thus, presenting an interesting opportunity for exploration (Kriner & Shen, 2014). In this study, we sought to determine predictors of congressional support of military action by using language as a predictor which is a common measure in studies of politics (Blaxill, 2013; Crew Jr & Lewis, 2011; Jarvis, 2004; Slatcher, Chung, Pennebaker, & Stone, 2007) and conflict (Kriner & Shen, 2014; Leudar, Marsland, & Nekvapil, 2004; Pennebaker, 2011). Furthermore, we explored if the most basic and objective components of language, word frequencies, could be used as practical predictors of support of conflict.

**Politics and Conflict**

A wide variety of predictor and outcome measures have been previously examined to determine the role of the executive in conflict. Clark and Nordstrom (2005) focused on political factors influencing the probability that an executive in a democracy would engage in conflict and found that low levels of citizen political participation, opposing party majority in the legislature, and greater legislative control of foreign policy was associated with lower probability that the executive would engage in conflict. Keller and Foster (2012) used leadership trait analysis, which is a content analytic method developed by Hermann (1987; as cited in Keller & Foster, 2012), to classify executives’ leadership style based on their language patterns and to examine how U.S. presidents’ locus of control related to their willingness to use military force abroad to divert attention from domestic problems. Keller and Foster found that presidents high in internal locus of control were more likely to engage military forces internationally and this relationship was mediated by domestic factors, such as the gross domestic product (GDP), indicating these presidents could use international conflict as a diversionary tactic. Leudar et al. (2004) used membership categorization analysis, which examines how people use words to identify with groups as well as to orient to events, in an exploration of how George W. Bush, Tony Blair, and Osama bin Laden used language to frame the events surrounding 9/11 and to orient to future action. All three leaders used language to set up an *us versus them* dichotomy, distinguishing allies and enemies; Bush and Blair used political and moral language to accomplish this separation, while bin Laden used religious language.

Turning to research on public opinion, Cohrs and Moschner (2002) conducted a study in Germany examining predictors of students’ attitudes toward the war in Kosovo, and they found militarism, diffuse political support, and authoritarianism predicted support for the war. They also found some evidence of confirmation bias whereas those who were against the war sought out information to strengthen that belief. McCleary et al. (2009) found similar results in a study of U.S. college students regarding support for the war in Iraq, and they found that blind patriotism (conceptually similar to diffuse political support), militarism, and concern for national security predicted continuing support for the war. A different study by Friese et al. (2009) found that political orientation predicted support for conflict in Iraq, but this relationship was mediated by attributions of responsibility for the war such that those who believed or were led to believe that U.S. leaders lied about weapons of mass destruction (WMDs) had much less support for the war.

Both the role of the legislative in conflict and individual word frequencies have been underexplored in their relationship to military conflict. Kriner and Shen (2014) studied speeches pertaining to the course of the Iraq War in the House of Representatives and found that antiwar rhetoric by Democrats increased as the number of casualties in the war increased, and specifically, the number of casualties from representatives’ districts. A speech was coded as antiwar if it argued that the initial invasion was a mistake or that troops should be withdrawn; for instance, if the congressman discussed causalities as unacceptably high or argued that the invasion was unjustified as Saddam Hussein posed no immediate threat, that speech was coded as antiwar. Furthermore, number of casualties also predicted antiwar voting by Democrats, and antiwar rhetoric by representatives was positively correlated with antiwar attitudes held by their constituents. In examining war discourse, Kriner and Shen only surveyed whether the overall content of each speech was prowar or antiwar not the specifics of the language used. Brett et al. (2007) examined individual word use but focused on resolutions in business conflicts. They found that greater use of negative emotion words, such as *hurt* or *hate*, and command words, such as *ought* or *must*, decreased the likelihood of conflict resolution while greater use of causal words, such as *because* or *hence*, and inhibition words, such as *constrain* or *stop*, increased the likelihood of conflict resolution. The current study combines these ideas by using the focus of the Kriner and Shen (2014) study, war rhetoric in Congress, and the methods of the Brett et al. study with word frequencies as predictors.

**Language**

Given the focus of word use in this study, it is imperative to establish that individual word use can be useful and meaningful. Discourse is the fusion of content and style words. Within any given sample of language, content words answer the question of what is being said, while style words answer the question how it is being said. Content words include mostly nouns, verbs, and adjectives, and style words include mostly pronouns, prepositions, articles, conjunctions, negations, and quantifiers (Pennebaker, 2011). The Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, & Francis, 2007) is a program developed to summarize these words and others broken down into 82 language categories. Besides style words, the LIWC measures constructs such as: a) cognitive mechanisms, such as *know*, *because*, and *none* reflecting causation, exclusivity, and certainty, b) social and emotional words, which include words reflecting social processes and positive and negative emotion, c) relativity, such as *go*, *down*, and *until* reflecting motion, space, and time, d) and personal concerns, which includes words reflecting achievement, money, death, and religion among others.

Discourse analysis has become a popular trend to understand psychological correlates tied to language. Tausczik and Pennebaker (2009) reviewed over a hundred articles that used language as a basis for studying other constructs; specifically, these studies investigated how categories in the LIWC are related to psychological phenomena, such as attention, emotionality, dominance, and deception. Reviewing these findings, Tausczik and Pennebaker discussed how pronouns and verb tense can demonstrate attentional focus by demonstrating who or what someone is attending to in a situation and how they are processing the situation. Therefore, greater use of first person pronouns indicated a self focus, third person pronouns indicated an focus on others, and verb tense indicated whether the focus was on past, present, or future events. Other studies they reviewed found that plural first person pronoun use positively correlated with social status, and these pronouns can be positively correlated with group cohesion except in situations where *we* is used to mean *you*. Several studies also found fewer singular first person pronouns, fewer third person pronouns, more motion, more negative emotion, and fewer exclusive words to be positively related to deception. Finally, Tausczik and Pennebaker found complexity in language to be linked to increased use of prepositions, cognitive mechanisms, and longer words.

Important to the current study are the findings pertaining to how language use can change in response to critical events. In a study of blogs following 9-11, Cohn, Mehl, and Pennebaker (2004) found that, in the two weeks following 9-11, writers of blogs tended to use more negative and social words as well as words indicating greater cognitive processing and greater psychological distancing. Psychological distancing and cognitive processes findings persisted for six weeks past 9-11 indicating that language analysis can be sensitive to long-term changes in thought processes. During an outbreak of swine flu, Tausczik, Faasse, Pennebaker, and Petrie (2012) discovered that blogs and online news outlets showed spikes in the use of death, health, and anxiety words as well as a dip in the use of positive emotion words persisting for two weeks. Pennebaker and Chung (2005) have provided a review of the literature on linguistic changes in response to terrorism and other negative events. A final study worth noting in this area includes Pennebaker’s (2011) analysis of language used by four Arabic-speaking terrorist groups (two violent, two nonviolent). He found that the violent terrorist groups used simpler words, more pronouns, less complex constructions, more emotional words, and more inclusive words as well as using language indicative of deception, status, and power. Pennebaker also examined how language used by these groups changed preceding a terrorist attack to determine how linguistic content could predict aggressive intent. Two to six months before an attack, groups used fewer prepositions, positive emotion words, and discrepancy words, while also using more motion and time words. One month before an attack, terrorist groups used more personal pronouns, prepositions, conjunctions, and inclusive words and fewer insight, causation, discrepancy, tentative, and exclusive words. These previous results provide support for applying these same language categories to predicting when member of the U.S. Congress are likely to support conflict.

**Political Discourse**

Language is a vital aspect of politics. Politicians use language to frame issues and change perspectives of voters (Bougher, 2012). Crew Jr and Lewis (2011) found that linguistic differences, specifically differences reflecting optimism, activity, and realism, predicted legislative success among state governors. Slatcher et al. (2007) discovered linguistic differences in presidential and vice presidential candidates in the 2004 election. Republican candidates used more presidential language, which was indicated by the use of articles, prepositions, positive emotion, and longer words. Democratic candidates used more depressive language, which was indicated by use of more first person singular pronouns, physical words, and negative emotion and fewer positive emotion words. Jarvis (2004) studied speeches from presidential candidates from the last half of the 20th century and portrayed that Democratic candidates tended use more discourse about political actors and their role in politics whereas Republicans tended to discuss more in the abstract about American ideals. Jarvis also found that Democratic candidates talked more about their constituent groups (i.e. labor unions, African Americans) whereas Republicans tended to talk more about the American group identity as a whole.

We can also use word analyses to explore war and conflict. Hogenraad (2005) established that an increased use of power words (i.e. *legitimate* and *terrorize*), and a decreased use of affiliation words (i.e. *family* and *thoughtful*) tended to precede war. Bugarski (2000) discussed the use of *us* versus *them* language, which often preceded and followed conflict as well as the use of euphemisms (e.g. *liberation* versus *invasion*) and hate speech to justify war. Crespo-Fernandez (2013) found that dysphemisms (euphemisms meant to invoke negative reactions) were an instrumental element of Churchill’s wartime speeches. Babones (2012) examined the rise of militarist language during the Iraq War with words such as *warrior* and *warfighter* increasing in popularity in the media. Esch (2010) explored how rhetoric in the form of politic myths has been used to legitimize the *war on terror* by perpetuating the notions of the U.S. being an *exceptional* nation with a *civilizing mission*. All of these findings have pointed to specific language used tied to war and conflict, which was investigated in this study using an underexplored sample of members of the U.S. Congress.

**Purpose and Hypotheses**

The purpose of this study was to determine the usefulness of language categories in predicting support for war for a previously ignored sample. We predicted that pronouns, verbs, and social/emotional words would be the most important linguistic categories in the following ways:

*Hypothesis 1*. Based on research by Leudar et al. (2004) and Bugarski (2000), we expected those who support military action to set up an *us* versus *them* dichotomy, and hence, an increased use of plural third person pronouns will predict greater probability to support military action.

*Hypothesis 2*. We expected verb tenses to predict changes in the probability of supporting military action because of a change in attentional focus (Tausczik & Pennebaker, 2009).

*Hypothesis 3*. Furthermore, based on the research by Pennebaker (2011) and Bugarski (2000), we expected that emotion words would predict changes in the probability of supporting military action: increased negative emotion words would predict greater probability of supporting military action, while more positive emotion words would predict less probability of supporting military action. Social and emotional words were placed together based on the social-emotional style constructed used in Pennebaker (2011).

*Hypothesis 4*. Finally, we expected that other style words such as linguistic processes, other function words (articles, prepositions), cognitive mechanisms, relativity, and personal concern words would be important in prediction though we made no directional predictions (Brett et al., 2007; Pennebaker, 2011).

**Method**

**Sample**

**Language samples.** Linguistic frequency analysis was conducted on political speeches gleaned from Congress. The source of language samples was the Congressional Record, a searchable database containing a record of each session of Congress since 1995. For this study, we searched for pertinent speeches from January 27, 1998 to September 19, 2013. Records were included if they pertained to U.S. relations with the following countries: Iraq, Libya, and Kosovo (see below for explanation of country selection). Samples were split by session date and person speaking, and therefore, each person could be represented multiple times in the dataset. From the Senate, 248 language samples were obtained (*N* = 198 Iraq, *N =* 50 Kosovo). These samples were obtained from 92 senators with 136 samples from Republican and 111 from Democrats. The mean word count was 1757.54 (*SD* = 1427.26, *mdn* = 1483.00), with a minimum word count of 124 and a maximum of 12215. From the House, 458 language samples were obtained (*N* = 331 Iraq, *N* = 106 Libya, *N* = 32 Kosovo). Libya was only included in the House data because the motion to authorize the use of military force in Libya failed in the House, and no voting record was available for the Senate. The House samples were obtained from 290 representatives with 211 samples from Republicans and 258 from Democrats. The mean word count was 757.54 (*SD* = 1135.55, *mdn =* 510.00), with a minimum of 97, and a maximum of 12165.

**Variables**

**Language.** Each language sample was analyzed using the Language Inquiry and Word Count (LIWC; Pennebaker et al., 2007). The LIWC analyzed text for 82 language categories. We examined eight language categories: Hypothesis 1: pronouns, Hypothesis 2: verbs, Hypothesis 3: social/emotional words, and Hypothesis 4: linguistic processes, other function words, cognitive mechanisms, relativity, and personal concerns. The pronouns category included first person singular and plural pronouns (*I, me, we*), second person pronouns (*you, your*), and third person singular and plural pronouns (*he, she, they*). The verbs category included past, present, and future tense verbs (*went, does, will*). The social/emotional category included social (*talk, mate*), positive emotion (*nice, love*), and negative emotion (*hurt, hate*) words. The linguistic processes category included percentage of dictionary and six letter words used in the speech along with average words per sentence. The other function words category included articles (*a, the*), adverbs (*very, really*), prepositions (*to, with*), conjunctions (*but, and*), negations (*no, not*), and quantifiers (*few, many*). The cognitive mechanisms category included insight (*think, know*), causation (*because, hence*), discrepancy (*should, would*), tentativeness (*maybe, perhaps*), certainty (*always, never*), inhibition (*constrain, stop*), inclusive (*with, and*), and exclusive (*but, without*) words. The relativity category included motion (*arrive, go*), space (*down, in*), and time (*end, until*) words. The personal concerns category included work (*job, majors*), achievement (*hero, win*), money (*cash, owe*), religion (*church, mosque*), and death (*bury, kill*) words.

**Military Action.** For the purpose of this study, military action was defined as military personnel being sent into another nation to coerce the actions of that nation. In the past 15 years, the U.S. has taken military action against Iraq, Afghanistan, Kosovo, and Libya, although Congress did not explicitly approve action in Afghanistan or Libya. Operational definitions for support for war were voting records (yay, nay) on bills authorizing military action for Iraq, Kosovo, and Libya (only voted on in the House). These bills were House Joint Resolution 114, 107th Congress (2002); Senate Concurrent Resolution 21, 106th Congress (1999); and House Joint Resolution 68, 112th Congress (2011).

**Data Analytic Technique.** The data collected include multiple language samples by the same senator and are structured by both party affiliation and region of interest. This structure was best analyzed with multilevel modeling, which allowed us to control for the correlated error terms of these three variables (senator, party, and region), if necessary. First, data were analyzed with no predictors to determine a null model for comparison. Next, data were analyzed by adding subsequent nesting components: senator, region, and party affiliation. The nested model with the lowest deviance scores was selected to then add independent variables to for testing. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log likelihoods are also provided as indicators of the best nested model, with lower scores indicating better fit for each index. The dependent variable was support for military action as described above. This variable was categorical (yay, nay), and therefore, logistic regression models were used to determine the odds ratio of each predictor along with Nagelkerke’s *R*2 for overall models. Type 1 error rate was controlled with in each hypothesis, thus making alpha *p* < .01 for Hypothesis 4.

**Results**

**Senate**

**Nesting.** Analyses were first conducted using only language samples from the U.S. Senate to determine which language categories could be useful in predicting support for military action. The nested models were tested as described in the data analytic section, and the optimal level of nesting indicated was by senator and region with the lowest deviance (*D* = 193.75), AIC (199.75), BIC (210.23), and Log likelihood scores (-96.87). Table I includes all Senate and House nested model tests.

**Hypothesis 1.** The pronoun model was found to be significantly better than the null model, Δ*D*(5) = 11.25, *p* = .05, RN2 = .09. Table II includes all overall model statistics for all four hypotheses. Of the individual predictors shown in Table III, only the singular third-person pronouns (*he*, *she*) were marginally significant (*B* = 1.55, *SE* = 0.87, *p* = .07, odds ratio (*OR*) = 4.72), which was not expected. The more senators used singular third-person pronouns, the more likely they were to support taking military action. Further analysis of separate word frequencies indicated that the singular third person pronouns used were mainly masculine, as they were used 40 times more often than feminine pronouns.

**Hypothesis 2-4.** Hypotheses 2 (verbs), 3 (social/emotional), and 4 (other, social/emotional, cognitive mechanisms, relativity, personal concerns) were not supported, *p*s = .12-1.00. See Table II for all relevant statistics.

**House of Representatives**

**Nesting.** The second analysis used language samples from the U.S. House of Representatives with the same data analytic procedure described above. The nested model by representative, region, and party affiliation had the lowest deviance (*D* = 527.97), AIC (535.97), BIC (552.45), and Log likelihood (-263.98), and therefore, all three variables were used for the following analyses. See Table I for all nesting statistics.

**Hypothesis 1.** The pronoun model for the House data was significantly better than the null model, Δ*D*(5) = 32.28, *p* < .001, *RN2* = .10, thus supporting our hypothesis in both data sets. Table II includes all overall model statistics for the four hypotheses. Again, the singular third-person pronouns remained the only significant predictor (*B* = 1.26, *SE* = 0.25, *p* < .001, *OR* = 3.52), as shown in bottom half of Table III. The more a representative used singular third-person pronouns, the more likely they were to support taking military action. Further analysis indicated that masculine pronouns were used 15 times more often than feminine pronouns, thus following the same pattern as the Senate data.

**Hypothesis 2.** Verbs were not a significant predictor of support for military action, Δ*D*(4) = 6.24, *p* = .18, *RN2* = .01.

**Hypothesis 3.** Hypothesis 3 was supported in the House data, as social/emotional words were better predictors than the null model, Δ*D*(3) = 9.55, *p* = .02, *RN2* = .03. Only social words were significant, (*B* = 0.18, *SE* = 0.06, *p* < .01, *OR* = 1.19). As social word usage increased, the more likely a representative was likely to support taking military action; however, this relationship was not as strong as the pronoun model. See Table IV for relevant statistics.

**Hypothesis 4.** The linguistic processes model was not different from the null model, Δ*D*(3) = 5.74, *p* = .13, *RN2* < .01, which matched the Senate data results. However, the House data provided interestingly different results in regards to the rest of Hypothesis 4 than the Senate data. The other function words model was significant, Δ*D*(6) = 44.73, *p* < .001, *RN2* = .13, indicating that articles (*B* = -0.42, *SE* = 0.10, *p* < .001, *OR* = 0.66), adverbs (*B* = -0.49, *SE* = 0.15, *p* = .001, *OR* = 0.61), negations (*B* = -1.01, *SE* = 0.24, *p* < .001, *OR* = 0.36), and quantifiers (*B* = -0.47, *SE* = 0.20, *p* = .02, *OR* = 0.63) were significant predictors of military action votes. As representatives increased their use of articles, adverbs, negations, and quantifiers, the less likely they were to support taking military action, and this relationship was strongest for negations (*no, not*). Table IV includes all predictor values.

The cognitive mechanisms model was also significant, Δ*D*(8) = 21.18 , *p* < .01, *RN2* = .07). In this analysis, only exclusive words were significant, (*B* = -0.44, *SE* = 0.18, *p* = .02, *OR* = 0.64). As words such as *but* and *without* were used more often, the less likely a representative was to vote to take military action. Next, the relativity model was different from the null model, Δ*D*(3) = 21.96, *p* < .001, *RN2* = .07. Motion (*B* = -0.51, *SE* = 0.20, *p* = .01, *OR* = 0.60), space (*B* = -0.23, *SE* = 0.11, *p* = .03, *OR* = 0.80), and time words (*B* = 0.54, *SE* = 0.13, *p* < .001, *OR* = 1.71) words were the significant predictors in this model. Representatives using more motion words, such as *go* or *arrive*, or space words, such as *down*, were less likely to support military action, and those who used more time words, such as *end* or *until,* were more likely to support military action. Lastly, the personal concerns model was better than the null model, Δ*D*(5) = 25.38, *p* < .001, *RN2* = .07. Interestingly, money (*B* = -1.24, *SE* = 0.31, *p* < .001, *OR* = 0.29) and death words (*B* = -0.54, *SE* = 0.21, *p* = .01, *OR* = 0.58) words were significant predictors of less support for military action.

**Discussion**

Our hypotheses were partially supported; however, the analyses revealed some interesting findings, which we did not expect. We hypothesized that the use of plural third person pronouns would predict support for military action as plural third person pronouns would seem to indicate taking an *us* versus *them* stance (Leudar et al., 2004). Instead, singular third person pronouns turned out to be a better predictor of voting for military action; as it was the only predictor significant in both samples, and the predictor with the largest effect size. The most probable reason for this finding is the change in the dynamics of war. Historically, the U.S. would declare war on another nation (i.e. fighting the Germans in WWI). In WWII, a slight shift occurred where the U.S. was fighting not only another nation but also an ideology (Nazi Germany, Fascist Italy). With the beginning of the Cold War, another movement happened where the U.S. did not directly fight another nation (USSR) but instead fought indirectly with proxy wars (Korean War, Vietnam War) while battling against enemy ideology (Communism). After the Cold War and the fall of the Soviet Union, the focus shifted to the United States’ main conflict being the *war on terror* (Matthews, 2014). Furthermore, Balas, Owsiak, and Diehl (2012) argued that one possible motivation for war, since the end of the Cold War, was the increased emphasis on the international norms of democratization and humanitarianism. Hence, the use of singular third person pronouns could reflect a focus on dictators violating human rights as a cause for conflict (i.e Hussein in Iraq, Milosevic in Kosovo, and Qaddafi in Libya). Furthermore, the use of masculine pronouns would seem to lend some support for this explanation.

Verb tense did not show a relationship with support for military action in either dataset, potentially because of the ebb and flow of conversation from past events to future action, thus creating an overall blanket use of many types of verbs. Another interpretation may be that even though members of Congress are focusing on the same events (therefore, no differences in verb tense), they are also directing attention on different people (thus, explaining differences in pronouns described above; Tausczik & Pennebaker, 2009). Social words were predictive for only the House of Representatives data, indicating that an increase in social words also lead to an increase in the likelihood of voting for military action. Social words included concepts such as *family, neighbor, friends,* and other relational descriptors. Conceivably, these words were used as a call to action to help support our *friends* and *neighbors* in other countries. On the other hand, based on the findings on group cohesion of Tausczik and Pennebaker (2009), the increase in the use of social words could reflect a need to protect the group (i.e. American citizens) from outgroup threats.

Next, we found that the increased use of articles, adverbs, negations, and quantifiers predicted a decrease in the probability a representative would support taking military action. This finding could indicate slightly more complex thinking from those who oppose war (Pennebaker, 2011). These styles words indicated that those who oppose military action used language that was concrete, descriptive, and inhibitive. The findings regarding exclusive, motion, and time words are similar to those in Pennebaker (2011). He found that aggressive intent was predicted by fewer exclusive words and more time words, and we found those words to predict support for war, potentially indicating aggressive intent in the House. However, for motion words, we found the opposite of Pennebaker’s work, where motion words associated with the opposition to war. We speculate that those who opposed military action focused on the enormity of the undertaking in conducting a war, thus, implying that the costs outweighed the benefits. Finally, an increase in money and death words predicted decreased support for military action. These results seem somewhat obvious, as it makes sense that those who focus on the cost of the war, both financial and human, would be less likely to support war.

**Limitations.** The sample and methods used in the study, while useful, can also be somewhat limited in scope. First, even though the Congressional Record represents everything said on the floor of Congress, it does not necessarily represent the entirety of Congress. Our sample incorporates nearly 15 years in Congress. This time period encompassed seven election cycles and at any given time, there are 100 senators and 435 congressmen and women. Yet, our data included only 92 unique senators and 290 congressmen and women. While our data set likely included speeches from the more influential senators and congressmen and women, we cannot predict voting from those who did not speak. Furthermore, our findings regarding masculine versus feminine pronouns could be confounded by the underrepresentation of women in Congress. In the 113th Congress, women comprised 20% of the Senate and 18% of the House (Manning & Brudnick, 2014). For the years of voting records we used, there were 96 women in Congress in 2011, 73 in 2002, and 67 in 1999 compared to 102 women in the current Congress. The other limitation was tied to using word frequency as an independent measure, although Tausczik and Pennebaker (2009) have provided support for this research. Word frequency is a meaningful measure of language, though it does fail to take into account context, sarcasm, and other subtle aspects of language.

**Future Directions.** While word frequency is an interesting and relatively easy method of linguistic analysis, other methods of content analysis could demonstrate usefulness in understanding support for war. The current study focused on the three most recent conflicts in Congress, but the next step might be to discover if pronoun use has changed in discussions of war in the last century. Finally, we studied the U.S. Congress because of a dearth in the literature, and studies of legislative bodies of other countries would be an excellent avenue to continue in this area. From the present study, it is clear that language can be a useful tool to further our understanding of the political process and its impact on war and peace.

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Table I.

*Nested Model Statistics for the Senate and House of Representatives.*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | *df* | Deviance | AIC | BIC | LogLik |
| Senate | Null Model | 242 | 305.02 | 307.02 |  |  |
| Senator | 151 | 217.14 | 221.14 | 228.12 | -108.57 |
| **Senator, Region** | **149** | **193.75** | **199.75** | **210.23** | **-96.87** |
| Senator, Region, Party | 147 | 199.51 | 207.51 | 221.46 | -99.75 |
| House | Null Model | 454 | 629.39 | 631.39 |  |  |
| Representative | 165 | 564.91 | 568.91 | 577.15 | -282.46 |
| Representative, Region | 162 | 564.12 | 570.12 | 582.49 | -282.06 |
| **Representative, Region, Party** | **160** | **527.97** | **535.97** | **552.45** | **-263.98** |

*Note*. Degrees of Freedom (*df*)*,* Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Log Likelihood (LogLik). Bolded lines represent the best nested model chosen for hypothesis testing analyses.

Table II.

*Senate And House of Representatives Model Fit for Hypothesis Tests.*

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Hypothesis | Test | *df* | Deviance | AIC | BIC | LogLik | ΔDeviance | Δ*df* | *p* | RN2 |
| Senate | 1 | **Pronouns** | **144** | **182.50** | **198.50** | **226.34** | **-91.25** | **11.25** | **5** | **.047** | **.09** |
| 2 | Verbs | 145 | 186.47 | 200.47 | 224.92 | -93.24 | 7.28 | 4 | .123 | .05 |
| 3 | Social/Emotional | 146 | 191.10 | 203.10 | 224.06 | -95.55 | 2.65 | 3 | .450 | .02 |
| 4 | Linguistic Processes | 146 | 188.01 | 200.01 | 220.97 | -94.00 | 5.74 | 3 | .125 | .04 |
| Other | 143 | 197.58 | 215.58 | 247.02 | -98.79 | 3.83 | 6 | 1.000 | .02 |
| Cognitive Mechanisms | 141 | 191.19 | 213.19 | 251.61 | -95.59 | 2.56 | 8 | .959 | .02 |
| Relativity | 146 | 190.13 | 202.13 | 223.09 | -95.06 | 3.62 | 3 | .305 | .02 |
| Personal Concerns | 144 | 191.31 | 207.31 | 235.25 | -95.65 | 2.44 | 5 | .785 | .02 |
| House | 1 | **Pronouns** | **155** | **496.68** | **513.68** | **550.77** | **-247.84** | **32.28** | **5** | **.001** | **.10** |
| 2 | Verbs | 156 | 521.73 | 537.73 | 570.69 | -260.86 | 6.24 | 4 | .182 | .01 |
| 3 | **Social/Emotional** | **157** | **518.42** | **532.42** | **561.26** | **-259.21** | **9.55** | **3** | **.023** | **.03** |
| 4 | Linguistic Processes | 157 | 527.30 | 541.30 | 570.14 | -263.65 | 0.67 | 3 | .880 | .01 |
| **Other** | **154** | **483.24** | **503.24** | **544.44** | **-241.62** | **44.73** | **6** | **.001** | **.13** |
| **Cognitive Mechanisms** | **152** | **506.79** | **530.79** | **580.23** | **-253.39** | **21.18** | **8** | **.007** | **.07** |
| **Relativity** | **157** | **506.01** | **520.01** | **548.85** | **-253.00** | **21.96** | **3** | **.001** | **.07** |
| **Personal Concerns** | **155** | **502.58** | **520.58** | **557.67** | **-251.29** | **25.38** | **5** | **.001** | **.07** |

*Note*. Change in deviance and *df* scores were calculated by subtracting the null model selected in Table 1 from the deviance scores of the current model. RN2 denotes Nagelkerke’s pseudo-*R2* for logistic regression models. Significant models have been bolded.

Table III.

*Hypothesis 1: Senate and House of Representative Pronoun Model Predictors*

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  | *95% CI B* | |  |  |  | | *95% CI Odds Ratio* | |
|  |  | *B* | *SE* | *Lower* | *Upper* | *z* | *p* | *Odds Ratio* | *Lower* | | *Upper* |
| Senate | Intercept | 11.71 | 3.57 | 4.72 | 18.71 | 3.28 | .001 |  |  | |  |
| I | -0.62 | 0.50 | -1.60 | .36 | -1.24 | .216 | 0.54 | 0.20 | | 1.44 |
| We | -1.21 | 0.72 | -2.61 | .20 | -1.69 | .092 | 0.30 | 0.07 | | 1.22 |
| You | 0.16 | 1.94 | -3.65 | 3.96 | 0.08 | .936 | 1.17 | 0.03 | | 52.39 |
| **He/She** | **1.55** | **0.87** | **-0.15** | **3.25** | **1.79** | **.073** | **4.72** | **0.86** | | **25.73** |
| They | 0.49 | 1.11 | -1.68 | 2.66 | 0.04 | .657 | 1.63 | 0.19 | | 14.30 |
| House | Intercept | -0.13 | 1.09 | -2.27 | 2.00 | -0.12 | .902 |  |  | |  |
| I | -0.01 | 0.14 | -0.27 | 0.26 | -0.03 | .973 | 1.00 | 0.76 | | 1.30 |
| We | -0.12 | 0.11 | -0.34 | 0.10 | -1.06 | .288 | 0.89 | 0.71 | | 1.11 |
| You | 0.27 | 0.54 | -0.79 | 1.33 | 0.50 | .615 | 1.31 | 0.45 | | 3.79 |
| **He/She** | **1.26** | **0.25** | **0.77** | **1.74** | **5.10** | **.001** | **3.52** | **2.17** | | **5.70** |
| They | 0.27 | 0.26 | -0.25 | 0.78 | 1.03 | .305 | 1.31 | 0.78 | | 2.19 |

*Note*. Bolded lines indicate significant predictors for pronoun models.

Table IV.

*Hypothesis 3 and 4 Individual Predictors for the House of Representatives Data*

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  | *95% CI B* | |  |  |  | | *95% CI Odds Ratio* | |
|  |  | *B* | *SE* | *Lower* | *Upper* | *z* | *p* | *Odds Ratio* | *Lower* | | *Upper* |
| Social/Emotional | Intercept | -1.80 | 1.24 | -4.22 | 0.62 | -1.46 | .146 |  |  | |  |
| **Social** | **0.18** | **0.06** | **0.05** | **0.30** | **2.84** | **.004** | 1.19 | 1.06 | | 1.35 |
| Positive Emotion | 0.12 | 0.13 | -0.13 | 0.37 | 0.94 | .348 | **1.13** | **.88** | | **1.44** |
| Negative Emotion | 0.18 | 0.11 | -0.04 | 0.40 | 1.59 | .113 | 1.19 | .96 | | 1.49 |
| Other Function | Intercept | 6.53 | 1.94 | 2.72 | 10.34 | 3.36 | .001 |  |  | |  |
| **Articles** | **-0.42** | **0.10** | **-0.62** | **-0.21** | **-4.01** | **.001** | **0.66** | **0.54** | | **0.81** |
| **Adverbs** | **-0.49** | **0.15** | **-0.79** | **-0.19** | **-3.19** | **.001** | **0.61** | **0.46** | | **0.83** |
| Prepositions | 0.05 | 0.09 | -0.12 | 0.22 | 0.57 | .570 | 1.05 | 0.88 | | 1.25 |
| Conjunctions | -0.01 | 0.12 | -0.24 | 0.23 | -0.04 | .968 | 1.00 | 0.79 | | 1.26 |
| **Negations** | **-1.01** | **0.24** | **-1.47** | **-0.55** | **-4.29** | **.001** | **0.36** | **0.23** | | **0.58** |
| **Quantifiers** | **-0.47** | **0.20** | **-0.87** | **-0.07** | **-2.28** | **.022** | **0.63** | **0.42** | | **0.94** |
| Cognitive Mechanisms | Intercept | 0.76 | 1.29 | -1.77 | 3.29 | 0.59 | .557 |  |  | |  |
| Insight | -0.06 | 0.15 | -0.35 | 0.23 | -0.39 | .698 | 0.94 | 0.71 | | 1.26 |
| Causation | 0.01 | 0.17 | -0.33 | 0.34 | 0.05 | .964 | 1.01 | 0.72 | | 1.41 |
| Discrepancy | 0.25 | 0.19 | -0.13 | 0.62 | 1.30 | .194 | 1.28 | 0.88 | | 1.86 |
| Tentativeness | -0.34 | 0.21 | -0.76 | 0.08 | -1.60 | .109 | 0.71 | 0.47 | | 1.08 |
| Certainty | -0.07 | 0.20 | -0.46 | 0.31 | -0.38 | .706 | 0.93 | 0.63 | | 1.36 |
| Inhibition | 0.34 | 0.20 | -0.05 | 0.74 | 1.69 | .091 | 1.41 | 0.95 | | 2.09 |
| Inclusive | 0.11 | 0.09 | -0.08 | 0.29 | 1.14 | .253 | 1.11 | 0.93 | | 1.34 |
| **Exclusive** | **-0.44** | **0.18** | **-0.80** | **-0.08** | **-2.38** | **.017** | **0.64** | **0.45** | | **0.92** |
| Relativity | Intercept | 0.79 | 1.28 | -1.70 | 3.29 | 0.62 | .535 |  |  | |  |
| **Motion** | **-0.51** | **0.20** | **-0.91** | **-0.12** | **0.20** | **.011** | **0.60** | **0.40** | | **0.89** |
| **Space** | **-0.23** | **0.11** | **-0.44** | **-0.02** | **-2.16** | **.031** | **0.80** | **0.65** | | **0.98** |
| **Time** | **0.54** | **0.13** | **0.28** | **0.80** | **4.08** | **.001** | **1.71** | **1.32** | | **2.22** |
| Personal Concerns | Intercept | 1.96 | 0.99 | 0.02 | 3.90 | 1.98 | .048 |  |  | |  |
| Work | 0.08 | 0.15 | -0.21 | 0.37 | 0.53 | .595 | 1.08 | 0.81 | | 1.44 |
| Achievement | -0.23 | 0.13 | -0.48 | 0.02 | -1.78 | .076 | 0.80 | 0.62 | | 1.02 |
| **Money** | **-1.24** | **0.31** | **-1.86** | **-0.63** | **-3.98** | **.001** | **0.29** | **0.16** | | **0.53** |
| Religion | 0.15 | 0.41 | -0.65 | 0.95 | 0.37 | .710 | 1.16 | 0.52 | | 2.59 |
| **Death** | **-0.54** | **0.21** | **-0.96** | **-0.12** | **-2.51** | **.012** | **0.58** | **0.38** | | **0.89** |

*Note*. Bolded lines indicate significant predictors within each model.