Same Words, Different Worlds:

Measuring Partisan Semantic Divergence in Congressional AI Discourse

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1. Introduction

The rapid advancement of artificial intelligence has thrust AI policy to the forefront of congressional debate. Yet as legislators from both parties increasingly engage with AI-related issues, a fundamental question emerges: when Democrats and Republicans use the same words to discuss AI, do they actually mean the same thing?

Political communication research has long recognized that partisan divides extend beyond policy preferences to the very language used in political discourse (Gentzkow & Shapiro, 2010). Studies of congressional speech have documented increasing linguistic divergence between parties over time (Gentzkow, Shapiro, & Taddy, 2019), while work on contested concepts suggests that politically charged terms like freedom or rights may carry fundamentally different meanings across ideological lines (Gallie, 1956). However, existing approaches typically measure polarization through topic differences—what each party talks about—rather than semantic differences in how they discuss shared concepts.

This study introduces a novel approach to measuring partisan polarization: semantic distance analysis using contextual word embeddings. Rather than asking whether Democrats and Republicans discuss different topics (they do), I ask whether they assign different meanings to the same words when discussing AI. Using 3,201 AI-related tweets from members of Congress (2018-2024) and a fine-tuned RoBERTa language model, I measure the semantic distance between Democratic and Republican usage of contested concepts like safety, rights, and regulation.

The findings reveal statistically significant semantic divergence: contested AI concepts show 1.78 times higher semantic distance between parties than neutral control words ($p = 0.024$, Cohen's $d = 0.99$). Qualitative analysis confirms these quantitative results—when Democrats discuss rights in AI contexts, they predominantly mean civil rights and collective protection; Republicans invoke individual rights and constitutional liberty. The word is the same, but the meaning differs substantially.

Beyond documenting semantic polarization, this study uncovers two additional patterns. First, semantic polarization appears to have decreased following ChatGPT's release in late 2022, with 73% of analyzed words showing convergence in the post-ChatGPT period. Second, the Senate exhibits 4.3 times greater semantic polarization than the House across all analyzed words. These findings suggest that AI policy debates may face a hidden challenge: legislators talking past each other while appearing to use shared vocabulary.

The remainder of this report proceeds as follows. Section 2 describes the data collection process and methodological approach, including the fine-tuning of domain-specific language models. Section 3 details the analytical methods employed, from embedding extraction to statistical validation. Section 4 presents results across four dimensions: aggregate semantic distance, qualitative collocation analysis, temporal trends, and chamber-level comparisons. Section 5 discusses implications for AI governance and directions for future research.

2. Data and Methods

2.1 Data Source and Collection

The primary data source is a comprehensive dataset of tweets from members of the United States Congress spanning 2018-2024. The original dataset contains 1,893,564 tweets from both chambers, collected via Nomic and compiled for academic research purposes. Each observation represents a single tweet, with associated metadata including the posting member's name, party affiliation (Democrat, Republican, or Independent), chamber (House or Senate), and timestamp.

2.2 AI-Related Tweet Filtering

To isolate AI-related discourse, I applied a comprehensive keyword filter using regular expressions with word boundaries to avoid false positives. The filter captured tweets containing terms including: artificial intelligence, AI (as a standalone term), machine learning, algorithm, ChatGPT, deepfake, facial recognition, autonomous vehicle, and related terminology. This filtering reduced the corpus from 1.89 million to 3,214 AI-related tweets.

2.3 Data Preprocessing

Several preprocessing steps prepared the data for analysis. First, I removed Independent party members to focus on the two-party partisan divide, yielding 3,201 tweets (2,022 Democratic, 1,179 Republican). Text cleaning preserved semantic content while removing noise: URLs were removed, RT prefixes stripped, and whitespace normalized. Importantly, I preserved original capitalization and punctuation, as the RoBERTa model was trained on naturally formatted text. Tweets shorter than 10 characters were excluded as uninformative.

The final dataset spans six years with notable temporal variation. AI discourse was minimal in 2018 (23 tweets) but exploded following ChatGPT's release, with 2023 (714 tweets) and 2024 (1,252 tweets) comprising 61% of all observations. Democrats consistently tweeted more about AI, though Republicans nearly matched Democratic volume in 2024 (509 vs. 743 tweets).

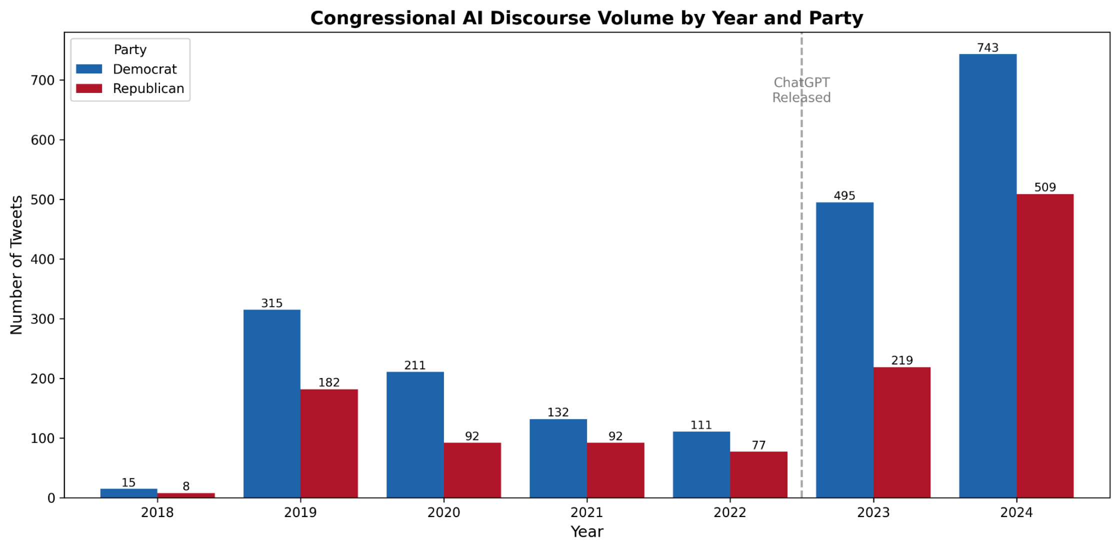

Figure 1: Congressional AI discourse volume by year and party. The dashed line indicates ChatGPT's release in November 2022.

2.4 Language Model Fine-Tuning

To capture domain-specific semantics, I fine-tuned a pre-trained RoBERTa-base model (124 million parameters) on the congressional AI tweet corpus. Unlike classification fine-tuning, I employed masked language modeling (MLM), which preserves the model's representation learning capabilities while adapting it to political AI discourse.

The fine-tuning procedure masked 15% of tokens in each tweet and trained the model to predict the masked words from context. Training proceeded for 3 epochs with a batch size of 16, learning rate of $2{\times}10^{-5}$, and fp16 mixed precision on a Tesla T4 GPU. Training loss decreased from 1.84 to 1.50 over approximately 2.5 minutes.

To verify domain adaptation, I tested the fine-tuned model's predictions for masked tokens in politically charged contexts. For the input China poses a [MASK] to American AI leadership, the model predicted threat with 92.78% confidence—demonstrating successful learning of political framing patterns that would not emerge from general-purpose language models.

2.5 Embedding Extraction

Using the fine-tuned model, I extracted 768-dimensional embedding vectors for each tweet. Following standard practice for sentence-level representations, I computed mean-pooled embeddings across all tokens, weighted by the attention mask to exclude padding tokens. This produced a dense vector representation capturing the semantic content of each tweet in the model's learned representation space.

3. Analysis

3.1 Semantic Distance Measurement

The core analytical approach measures semantic distance between Democratic and Republican usage of shared vocabulary. For each target word (e.g., safety), I identified all tweets containing that word, separated them by party, and computed the centroid (mean embedding vector) for each party's tweets. The semantic distance is then calculated as 1 minus the cosine similarity between party centroids. Higher values indicate greater semantic divergence—the same word appears in more dissimilar contexts across parties.

3.2 Word Selection

I analyzed two categories of words. Contested concepts (n=11) are policy-relevant terms hypothesized to carry different meanings across parties: safety, regulation, risk, rights, security, privacy, innovation, jobs, technology, protect, and transparency. Control words (n=10) are neutral terms expected to show minimal semantic divergence: today, year, congress, bill, act, work, time, need, american, and important.

3.3 Statistical Validation

To ensure robust inference, I employed multiple validation strategies. Permutation testing randomly shuffled party labels 10,000 times to generate a null distribution, with p-values representing the proportion of permuted distances exceeding the observed distance. Bootstrap confidence intervals were calculated by resampling tweets with replacement 1,000 times within each party. Robustness checks verified results using alternative distance metrics (Euclidean, Manhattan) and confirmed near-perfect rank correlations (Spearman $\rho > 0.98$) with cosine distance results.

3.4 Qualitative Analysis

To understand how meanings differ, I conducted collocation analysis—extracting the most frequent bigrams containing each target word, separated by party. This reveals the associative contexts that shape word meaning. Additionally, I trained a logistic regression classifier to predict party from tweet embeddings, then projected individual tweets onto the learned partisan axis to visualize within-word distributions (SemAxis analysis).

3.5 Temporal and Subgroup Analysis

To assess whether semantic polarization is changing over time, I compared semantic distances before and after ChatGPT's release (November 2022). I also examined variation across congressional chambers (House vs. Senate) and identified individual members whose discourse most strongly exemplifies partisan framing.

4. Results

4.1 Baseline Topic Differences

Before examining semantic divergence, I confirmed that Democrats and Republicans discuss AI differently at the topic level. Log-odds ratio analysis of word frequencies reveals distinct framing priorities. Democratic discourse emphasizes civil rights, discrimination, workers, and algorithmic bias—a frame centered on AI's potential harms to vulnerable communities. Republican discourse emphasizes China, the CCP, national security, and adversaries—a frame centered on geopolitical competition.

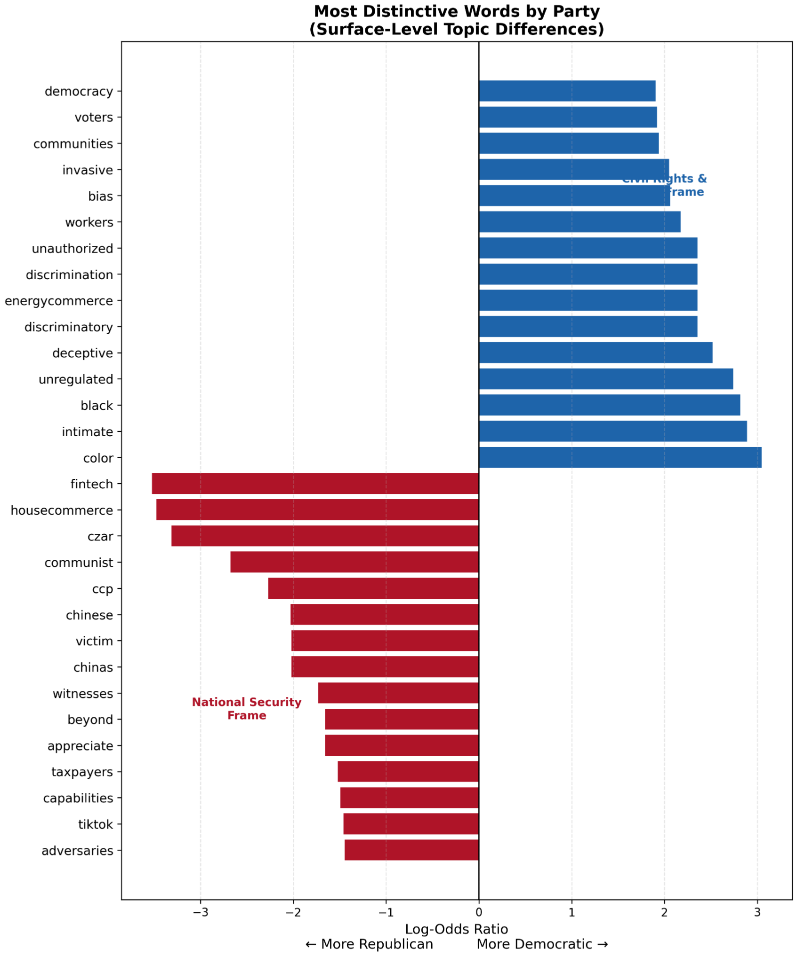

Figure 2: Log-odds ratio of word usage between parties. Positive values indicate Republican-leaning terms; negative values indicate Democratic-leaning terms.

These topic differences set the stage for the central question: beyond talking about different things, do parties mean different things when using shared vocabulary?

4.2 Semantic Divergence in Contested Concepts

The core finding confirms the study's hypothesis: contested concepts show significantly higher semantic distance than control words.

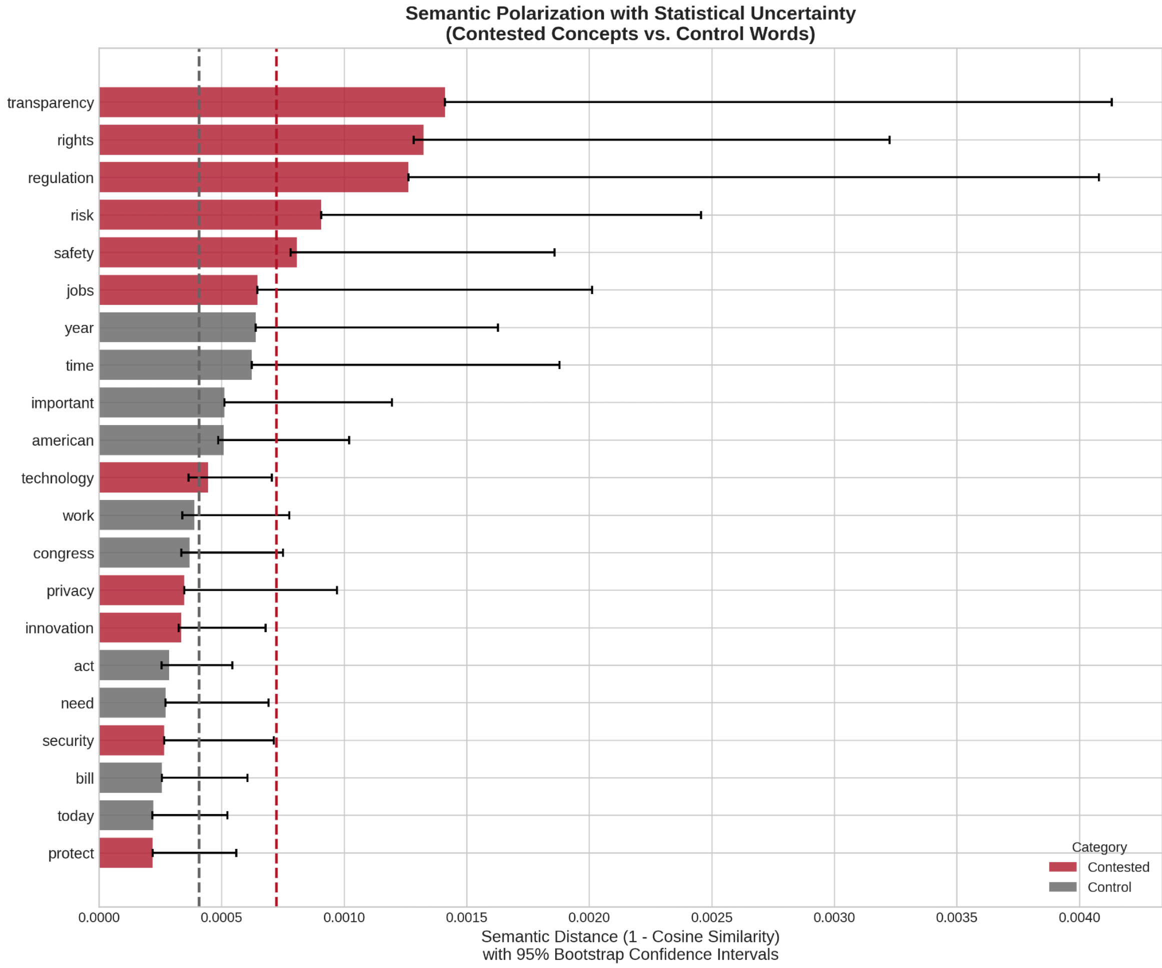

Figure 3: Semantic distance between Democratic and Republican usage of contested concepts (red) versus control words (gray), with 95% bootstrap confidence intervals.

Contested words average 0.000724 semantic distance compared to 0.000408 for control words—a ratio of 1.78. Permutation testing confirms this difference is statistically significant ($p = 0.024$), and the effect size is large (Cohen's $d = 0.99$). The most semantically polarized words are: (1) Transparency (0.0014), (2) Rights (0.0013), (3) Regulation (0.0013), (4) Risk (0.0009), and (5) Safety (0.0008).

Notably, some contested words show minimal divergence. Security (0.00027) and protect (0.00022) exhibit distances comparable to control words, suggesting potential areas of bipartisan semantic agreement.

4.3 Partisan Axis Classification

A logistic regression classifier trained to predict party from tweet embeddings achieves 72.1% accuracy (5-fold CV: 70.2% ± 2.1%), substantially exceeding the 50% random baseline. This confirms that despite visual overlap in dimensionality-reduced projections, embeddings encode learnable partisan signal.

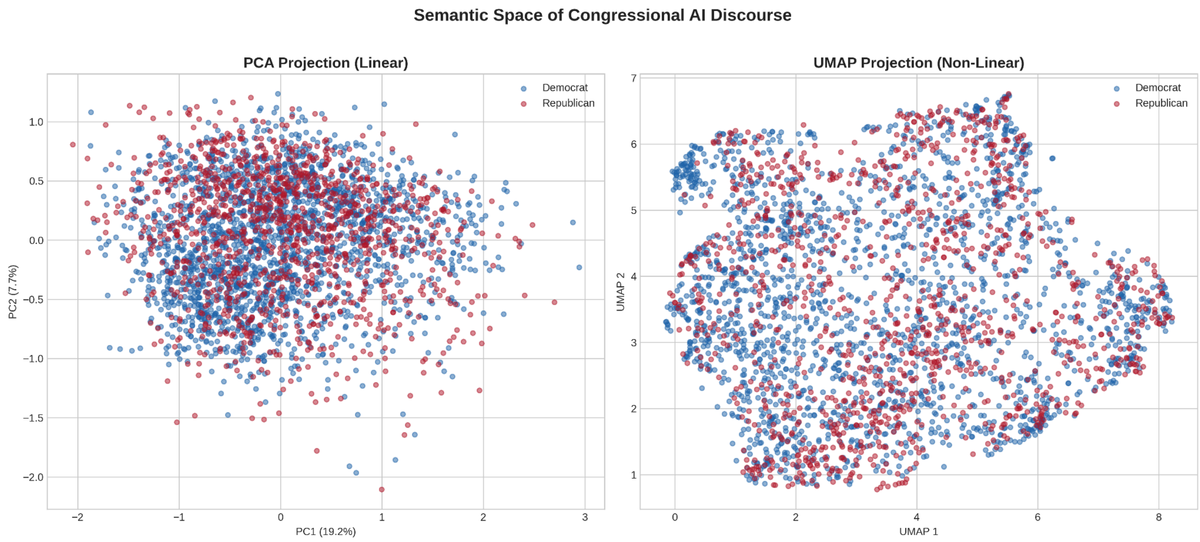

Figure 4: Dimensionality-reduced visualization of tweet embeddings (PCA and UMAP). While parties overlap substantially, the classifier identifies separable structure in the full 768-dimensional space.

4.4 Qualitative Evidence: How Meanings Differ

Collocation analysis reveals the specific associative patterns driving semantic divergence.

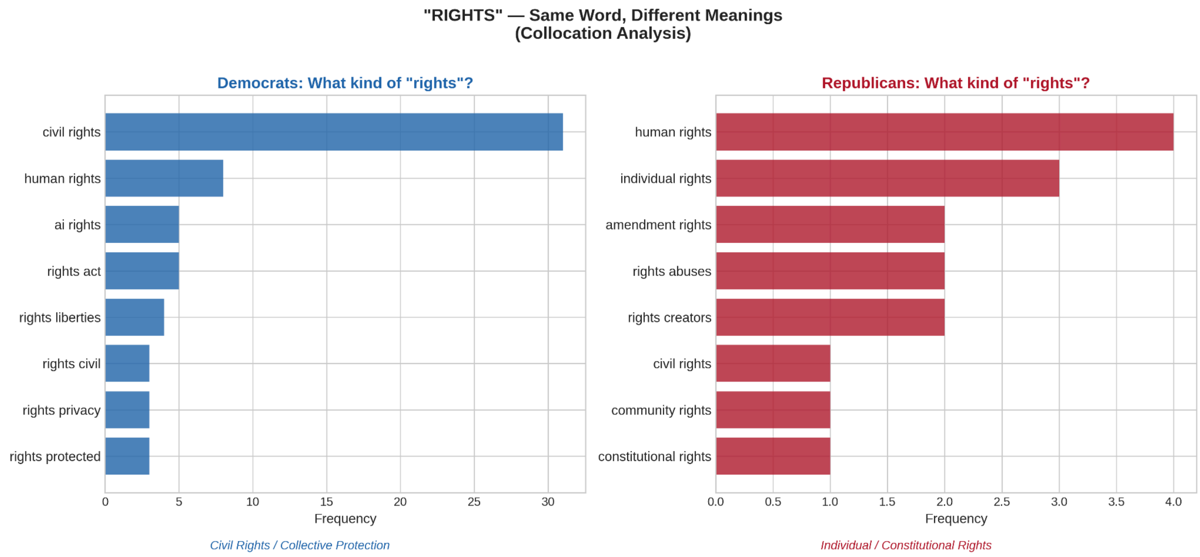

Figure 5: Collocation analysis for rights. Democrats predominantly use civil rights (31 occurrences) while Republicans use individual rights, amendment rights, and constitutional rights.

The contrast is striking: Democratic usage connects AI rights discourse to the civil rights tradition and collective protection from discrimination. Republican usage invokes constitutional liberties and individual freedom from government overreach. Both parties discuss rights in AI policy, but the underlying conceptual frameworks differ fundamentally.

Similar patterns emerge for other contested words. For regulation, Democrats collocate with comprehensive, fair, and oversight—framing regulation positively as necessary protection.

Republicans collocate with burdensome, excessive, and government—framing regulation as impediment to innovation. For safety, Democrats emphasize standards and ensure safety—an approach centered on mandatory protections. Republicans reference alignment and product safety—a more technical, market-oriented framing.

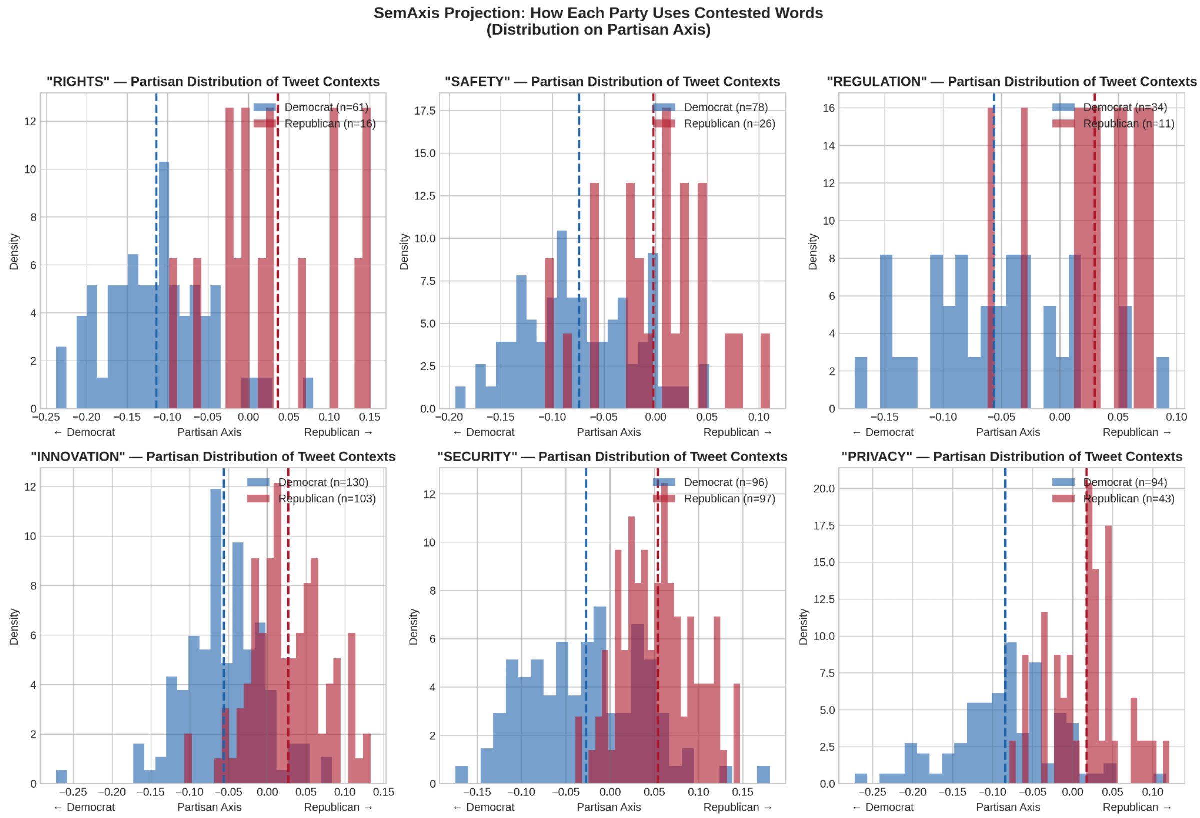

Figure 6: SemAxis distributions showing how individual tweets containing contested words distribute along the partisan axis. Rights shows strong separation while security shows substantial overlap.

4.5 Temporal Trend: The ChatGPT Effect

Comparing pre-ChatGPT (2019-2022) and post-ChatGPT (2023-2024) periods reveals an unexpected pattern: semantic polarization appears to have decreased following ChatGPT's release.

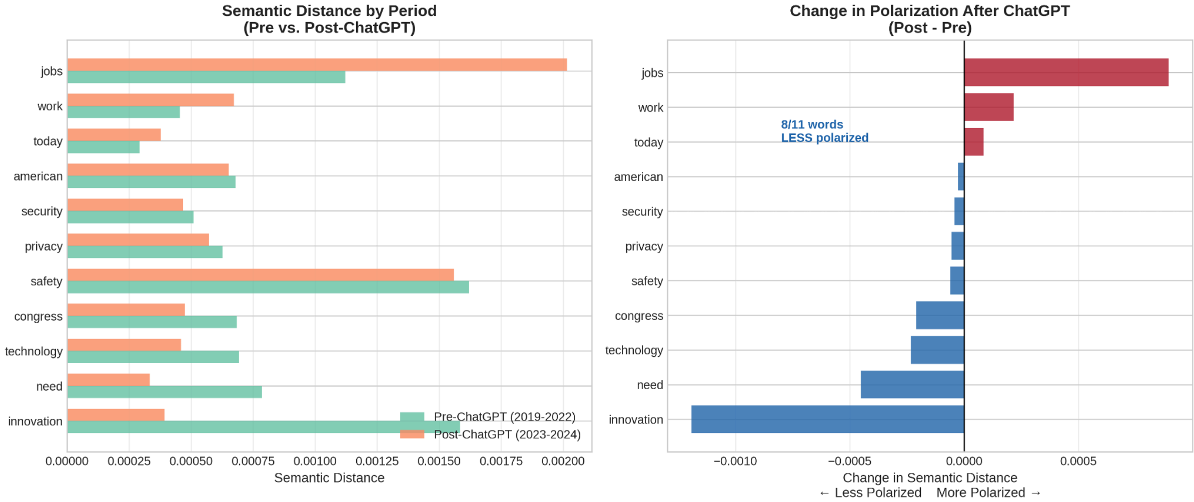

Figure 7: Change in semantic distance from pre-ChatGPT to post-ChatGPT periods. Blue bars indicate decreased polarization; red bars indicate increased polarization.

Eight of eleven words (73%) show decreased semantic distance in the post-ChatGPT period. The largest convergence appears in innovation (-0.0012), followed by need (-0.0005) and technology (-0.0002). Only jobs (+0.0009) shows substantial divergence increase.

While statistical tests do not reach conventional significance (Wilcoxon p = 0.18) due to limited sample size, the consistent pattern suggests ChatGPT may have created a shared reference point that brought partisan AI discourse closer together semantically. Both parties now discuss AI with ChatGPT as a common touchstone, potentially reducing the degree to which they talk past each other.

4.6 Chamber Comparison: Senate vs. House

Subgroup analysis reveals striking differences between congressional chambers. Senate AI discourse is 4.3 times more semantically polarized than House discourse (0.000427 vs. 0.000099). This pattern holds consistently across all analyzed words—every word with sufficient data in both chambers shows higher Senate polarization.

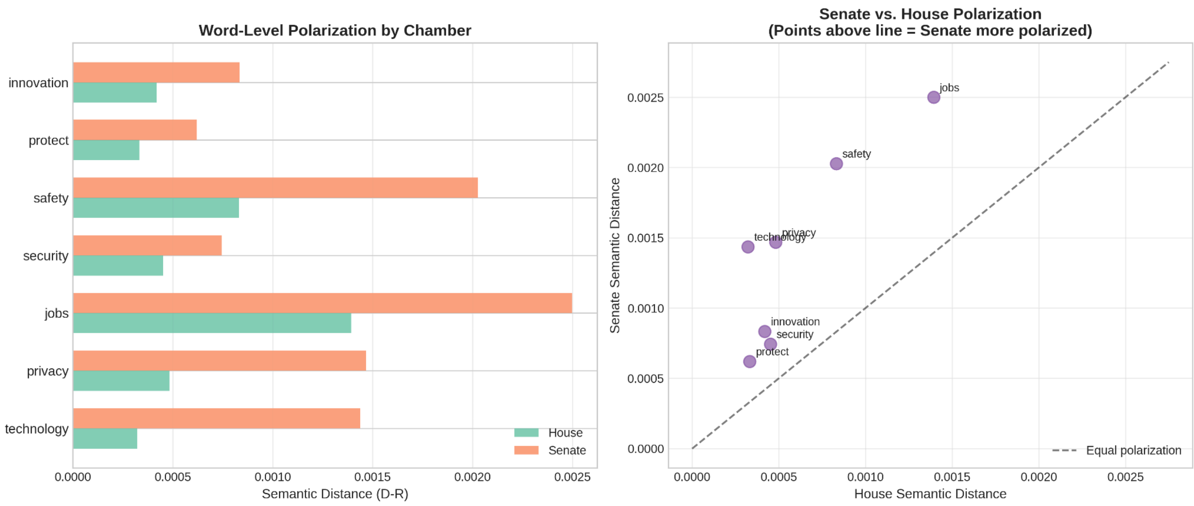

Figure 8: Semantic polarization by chamber. Left panel shows word-level comparison; right panel confirms all points fall above the equal-polarization diagonal.

Several factors may explain this chamber difference. Senators represent larger, more diverse constituencies and serve longer terms, potentially encouraging more ideologically distinct positioning. The Senate's higher media profile may also incentivize sharper partisan differentiation in public communications. Alternatively, the House's larger membership may produce more heterogeneous within-party discourse that averages to smaller between-party distances.

4.7 Individual Speaker Analysis

Finally, I identified which members most strongly exemplify partisan semantic framing. Among Democrats, progressive members lead: Robert Casey (PA), Pramila Jayapal (WA), Ayanna Pressley (MA), and Rashida Tlaib (MI) show the most Democratic-leaning AI discourse. Among Republicans, Jim Banks (IN), John Cornyn (TX), and Josh Hawley (MO) show the most Republican-leaning discourse.

Notably, Democratic extremes are more pronounced than Republican extremes (mean scores of -0.14 vs. +0.06), suggesting progressive Democrats may drive semantic polarization more strongly than their conservative Republican counterparts in AI discourse specifically.

5. Discussion

5.1 Summary of Findings

This study demonstrates that partisan polarization in AI policy extends beyond topic selection to the meanings of shared vocabulary. Contested concepts like rights, regulation, and safety carry significantly different semantic content when used by Democrats versus Republicans. This semantic divergence is statistically robust, validated across multiple methods, and supported by qualitative evidence showing distinct associative patterns.

Three additional findings enrich this core result. First, semantic polarization appears to have decreased following ChatGPT's release, suggesting that salient shared experiences may create common ground even in polarized discourse. Second, the Senate exhibits substantially greater semantic polarization than the House, pointing to institutional factors that may amplify or attenuate linguistic divergence. Third, progressive Democrats drive semantic polarization more strongly than conservative Republicans in this domain.

5.2 Contributions

This study makes three contributions to the literature on political polarization and computational text analysis. First, I introduce semantic distance measurement as a complement to existing approaches that focus on topic divergence or sentiment. By asking not just what parties discuss but what they mean, this approach captures a previously unmeasured dimension of political division.

Second, I demonstrate the value of domain-adapted language models for political text analysis. Fine-tuning on the target corpus enables the model to capture domain-specific semantic patterns (e.g., China to threat) that general-purpose models would miss.

Third, the finding that ChatGPT's release coincided with semantic convergence suggests a potential mechanism for reducing polarization: shared reference points that anchor discourse across partisan lines. This has implications for how major technological developments may shape political communication.

5.3 Implications for AI Policy

The findings carry practical implications for AI governance. If legislators use the same words but mean different things, policy negotiations may face hidden obstacles. A Democrat proposing AI safety regulation may envision comprehensive standards protecting civil rights, while a Republican hearing the same phrase may interpret it as burdensome government overreach threatening innovation.

This suggests that effective AI governance requires explicit definition of contested terms. Rather than assuming shared vocabulary implies shared understanding, policymakers should articulate precisely what they mean by safety, rights, and regulation in specific contexts. The relatively low polarization around security suggests this may be an area where bipartisan agreement is more achievable.

5.4 Limitations and Future Directions

Several limitations warrant acknowledgment. First, Twitter/X data may not represent legislators' full range of AI discourse; floor speeches and committee hearings may show different patterns. Second, the sample of contested words was researcher-selected; future work could identify contested concepts empirically. Third, the temporal analysis lacks statistical power due to limited pre-ChatGPT data; longer time series would strengthen causal inference.

Future research could extend this approach in several directions. Comparing semantic polarization across policy domains (AI vs. healthcare vs. climate) would reveal whether the patterns observed here are AI-specific or reflect broader polarization dynamics. Analyzing other political actors (media outlets, advocacy groups) would show whether congressional patterns propagate through the broader discourse ecosystem. Finally, experimental studies could test whether semantic divergence actually impedes policy negotiation, establishing the real-world consequences of talking past each other while using the same words.

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