Categorizing topics versus inferring attitudes: a theory and method for analyzing open-ended survey responses

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Abstract

Past work on closed-ended survey responses demonstrates that inferring stable political attitudes requires separating signal from noise in "top of the head" answers to researchers' questions. We outline a corresponding theory of the open-ended response, in which respondents make narrow, stand-in statements to convey more abstract, general attitudes. We then present a method designed to infer those attitudes. Our approach leverages co-variation with words used relatively frequently across respondents to infer what else they could have said without substantively changing what they meant – linking narrow themes to each other through associations with contextually prevalent words. This reflects the intuition that a respondent may use different specific statements at different points in time to convey similar meaning. We validate this approach using panel data in which respondents answer the same open-ended questions (concerning healthcare policy, most important problems, and evaluations of political parties) at multiple points in time, showing that our method's output consistently exhibits higher within-subject correlations than hand-coding of narrow response categories, topic modeling, and large language model output. Finally, we show how large language models can be used to complement – but not, at present, substitute – our "implied word" method.

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1 Introduction

Classic theories of the survey response in political science (Zaller 1992; Zaller and Feldman 1992) hold that most people have weak preferences on specific policy proposals and so give unstable responses to closed-ended items based on what happens to be at the "top of the head." Partly due to concerns about top-of-the-head responding and other response artifacts, open-ended items can be a useful complement to their restricted, closed-ended counterparts. They allow for broader reflections of how respondents think about politics and their own beliefs (Schuman and Scott 1987; Feldman and Zaller 1992; Kraft 2023) and can sometimes be used to sidestep closed-ended response style effects (Hobbs and Ong 2023).

Open-ended responses have until recently been difficult to analyze at scale, though recent advances in natural language processing now allow for efficient document classification and categorization – with or without supervision from human labels (Yin et al. 2019; Miller et al. 2020; Mellon et al. 2022; Gilardi et al. 2023). However, these advances have been concentrated in applications where researchers know how documents ought to be evaluated in advance – whether they reference specific constructs or meet specific criteria of interest[1] – or in supervised settings where differences in word use can be directly linked to an observed outcome such as respondent partisanship. Furthermore, methodological advances do not by themselves address deeper theoretical questions regarding the relationship between the respondent's underlying attitudes and what they express on a survey. If capturing stable expressions of political attitudes is the goal – which can then inform researchers' choices regarding *what* to label – methods for analyzing open-ended responses must be grounded in a theory of the open-ended survey response.

We argue that open-ended survey responses represent top-of-the-head expressions of more

[1]Recent work using LLMs for text scaling, for example, prompts the model to compare documents with respect to a researcher-supplied construct such as left/right ideology (Wu et al. 2023).

general attitudes – much like closed-ended responses. In our theory of the open-ended survey response, respondents first choose a high-level attitude to express in their answer. Because that general attitude may be abstract and difficult to express in words, they then come up with a more specific statement that is easier to communicate. This statement is an incomplete stand-in for a broader attitude – in the language of the closed-ended survey response, a sampled consideration from a underlying attitudinal distribution. Importantly, this means that the ability to accurately and narrowly classify what a respondent happened to say in an open-ended response will not necessarily be the same thing as capturing the broader attitude they expressed (or are likely to express again). The latter requires inferring the more general distributions from which specific statements were sampled – an inherently unsupervised task toward which pre-trained language models have not thus far been oriented. Practically speaking, this involves inferring a range of statements that could be substituted for what someone happened to say without changing what they generally mean – such that we can predict what they are likely to express in response to the same question later on.

With our theory in mind, we show that it is possible to use text data to infer which elements of open-ended responses are more likely to reflect stable response patterns and, in line with longstanding theories of the survey response in political science, are more likely to reflect the range of political attitudes expressed in a corpus (though not guaranteed to, as we'll discuss and evaluate). If many respondents use the same words when giving statements, and those words are associated with relatively polarizing sets of less frequently-used words, then those "contextually common" words may provide useful signals of the attitudes being expressed – even if they'd appear vague in more general contexts. In this, we leverage two premises about words used unusually frequently in political contexts: 1) they are re-used across a broad range of more narrow political statements that respondents tend to substitute for each other (and so they can be used to link those statements) and 2) when these words are used in politically distinct ways, they can take on symbolic and polarized meanings.

For example, the average meaning of the word 'people' in a focused political context may be closer to meanings like 'the people', 'working people', or 'ordinary people' than its more general meaning – implying senses of the word that exclude (and place 'the people' against) 'politicians' and 'the rich' (or, in some cases, out-partisans and racial out-groups). Using such a word can both convey meaningful political attitudes and also bridge sets of less common statements.

It is important to clarify that our claim is that contextually common words are particularly useful for inferring distributions of attitudes at the corpus level. At the document level, a person using common rather than rare words to express the same attitude *does not* necessarily mean that they have a more stable underlying attitude (they might, but that is unrelated). Three different respondents who strongly disapprove of the Affordable Care Act may articulate this disapproval using different specific terms (such as 'free enterprise,' 'individual mandate,' or 'socialism'). We can infer that they intend to convey similar meaning through these terms' co-occurrence with words used across multiple respondents (such as 'government', as in 'big government').

The usefulness of contextually common[2] words may seem counter-intuitive to many text-as-data practitioners. There are almost certainly *more* rare words that are predictive of attitudes, and in a supervised setting these could be used to classify many specific outcomes. However, this can be easily driven by the far greater number of unique rare words compared to common ones overall (i.e., Zipf's law) and a resulting base rate fallacy in evaluating the *average* importance of contextually common versus rare words. It is easy to identify a small number of rare words that are highly correlated with an outcome of interest, even when they are the exception rather than the norm. Without a known filter for uninformative rare

[2]By contextually common we mean words that are often used to answer a specific prompt (e.g., "government"), which are far more informative in open-ended settings than words used frequently across all contexts (e.g, "I").

words – and (in line with our goals here) a reliable means to link informative terms to more abstract concepts – many rare words will reflect a variety of idiosyncratic considerations that happened to be salient for the respondent at the time (i.e., what a respondent happened to think of when they answered the question), *in addition to* a core attitude that is more likely to be expressed in repeated measures.

Consistent with this theory, we show that 1) words commonly used to answer a focused open-ended prompt – as well as more prevalent human-coded categories – tend to be more strongly correlated over survey waves than rare ones; and 2) a method explicitly leveraging variation in contextually common word use to infer distributions of (polarized) statements provides efficient quantitative representations of open-ended responses. Our method outperforms other tools, especially topic models, in terms of both test-retest reliability and in predicting high-level groupings of hand labeled political content.

After showing this performance, we provide recommendations for use of our approach – and words of caution. Although the method returns stable dimensions of responses, these dimensions are not guaranteed to conform to researcher expectations (such as recovering a left/right dimension, as many alternate scaling methods for behavioral data aim to – often by training on a subset of a data set that is more likely to be driven by left/right ideology). For example, it is possible for the primary variation in an open-ended response to be communication style, just as a closed-ended responses can be dominated by social desirability or acquiescence bias. As with any automated text method, ours requires in-depth validation of its output. The method also does not reveal all topics that can be labeled in a data set – just the ones that tend to be the most stable over time. As Grimmer et al. (2022) note, there is no globally optimal method when it comes to analyzing text as data.

Finally, we extend our method to demonstrate its practical usefulness in tandem and in comparison with common alternatives. We first provide a technique to describe the context-

specific and potentially symbolic meanings of common words. We then demonstrate how our method's output relates to that of tools like topic models and principal component analysis on the latest generation of contextualized embeddings. We find that these off-the-shelf methods *can* – at times and under favorable conditions – recover similar information as ours. However, in our analyses, the most reliable means to find topics and embeddings dimensions with high test-retest reliability and the strongest correspondence with sets of hand labels is to assess correlations with the top dimension of our method's output.

2 Background

Representative democracy assumes that citizens have meaningful attitudes on political matters that can be communicated to and considered by their representatives (Pitkin 1967; Mansbridge 2003). Without attitudes, and the ability to identify them with some degree of regularity, "democratic theory loses its starting point" (Achen 1975).

Early scholars of U.S. public opinion were skeptical that most citizens held political attitudes at all (Converse 1964, 1970). However, subsequent work (e.g., Achen 1975) salvaged the attitude in political science by highlighting a distinction between attitudes in survey respondents' minds and attitudes measured with (hopefully random) error in surveys. Rather than expecting a one-to-one correspondence between attitudes and survey responses, it is more useful to consider attitudes as unobserved, probabilistic distributions and survey responses as draws from those distributions. Statistical techniques that account for the measurement error inherent to the individual survey response, often by leveraging responses from multiple related items, allow us to learn more about the latent distributions of attitudes that produced them (Ansolabehere et al. 2008; Fowler et al. 2022).

The (Closed-Ended) Survey Response

The dominant model of the survey response in political science, Zaller's (1992) Receive, Accept, Sample (RAS) model, incorporates these perspectives to account for empirical regularities in mass opinion research. In this model, individuals receive varying amounts of information about political matters, accept or reject that information based on their political predispositions, and sample from "considerations" – or discrete elements of relevant information – that they have previously accepted when they encounter questions on surveys. The survey response is interpreted as an average of the considerations that were accessible to the respondent when they answered.

Especially for the majority of citizens who do not pay close attention to politics, responses are often constructed on the fly, and based on whichever considerations happen to be available when questions are posed. As many citizens hold considerations that carry divergent implications for matters of public policy – they may, for example, value both freedom and equality (Feldman and Zaller 1992) or civil rights and public safety (Nelson et al. 1997) – contextual factors that influence which considerations are made salient can alter responses to similar or even identical questions (Asch 1940; Wilson and Hodges 1992).

Open-Ended Responses

The typical mass opinion survey, for which the RAS model was designed, involves closed-ended survey items in which the respondent selects from a pre-determined list of potential answers to each question. Open-ended responses do not similarity limit response options, but the task of mapping articulated responses to underlying attitudes remains challenging. Qualitative categorization of open-ended responses often do not match closed-ended responses to otherwise similar questions (Schuman and Presser 1979; Schuman and Scott 1987), and researchers' interpretations of respondents' answers can differ from those of the

respondents themselves (Glazier et al. 2021).

Nonetheless, past (largely qualitative) work on open-ended responses suggests that this mapping is in principle feasible. When posing obscure and almost certainly unfamiliar policy proposals to respondents, Schuman and Presser (1980) found that many who could not be said to have a preference on the specific proposal nevertheless tried to use the opportunity to convey a more general attitude.[3] In their analyses of open-ended responses, Zaller and Feldman (1992) identified a dizzying number of different "frames of reference" respondents used to approach different policy proposals, but the vast majority of responses had a clearly-identifiable "directional thrust" that reflected their more general disposition.

Theory of the open-ended survey response

Our theory of the open-ended response broadly follows the RAS model (Zaller 1992) in that we assume responses represent top-of-the-head expressions of accessible considerations when evaluating the 'attitude object' given by a prompt, but differs in the relationship between sampled considerations and the eventual response. In closed-ended responses, some considerations may be more accessible than others, but respondents still average across those that come to mind before selecting a response option. For open-ended responses, we argue that 1) some *parts* of the responses reflect considerations that are more chronically accessible, and are therefore likely to have served as the starting point for the respondent; 2) it is possible infer these more accessible parts of responses when studying text (even without panel data, though it's better to have it); and 3) these more accessible considerations better reflect what could be recognized as stable attitudes.

In our model, the respondent begins with an initially drawn directional thrust. They then

[3]Schuman and Presser (1980) analyzed closed-ended responses in combination with interviewers' records of comments respondents made when answering them.

sample specific, related considerations in order to satisfy the expectations of a composed response, and to communicate their attitude sincerely and efficiently. While some respondents may have more to say than others, they will still not cover every topic they could have discussed and may elaborate on a single, sampled topic consistent with the thrust of their attitude.

In this setting, we expect that words used relatively frequently in the context of the survey prompt (though not necessarily words used frequently across all contexts; see Figure F.1, which shows that these words are *moderately* common in American English) are likelier than rare words to reflect the directional thrust of responses. This is at least in part because contextually common words are likelier to reflect symbolic language, which allows the respondent to efficiently convey a large amount of topic-dependent meaning. Symbolic language is extremely common in politics, as political elites and the citizens who take cues from them contest and reshape the meaning of particular words and phrases in specific political contexts (Lasswell et al. 1952; Edelman 1985; Neuman et al. 1992). For example, when someone asked to explain why they oppose the Affordable Care Act says that they object to "big government," we do not necessarily expect that they are articulating a broadly libertarian ideology that would extend to other issue contexts such as military spending. We instead understand their use of the term to symbolize objections to redistribution and new government interventions into the private health insurance market – and we can do so because "government" is mentioned relatively frequently when people express their (negative) attitude toward the Affordable Care Act. There are a variety of different ways people express this more general attitude, and in context we would understand any of these specific expressions to convey a similar meaning.

Especially in short text settings, such as open-ended survey responses, we expect people to rely on symbolic language to express their attitudes efficiently. For example, even if respondents would have trouble precisely defining "big government," we can still infer what

they mean based on how other people tend to use it in similar contexts. Frequently used words that have many context-specific associations, both in terms of words they regularly appear with and words they consistently do *not* appear with, are therefore likelier to reflect general political attitudes. This intuition is reflected in Figure 1, where multiple related terms are linked through their shared relationship with the word "government", and we provide example responses in SI Section G.

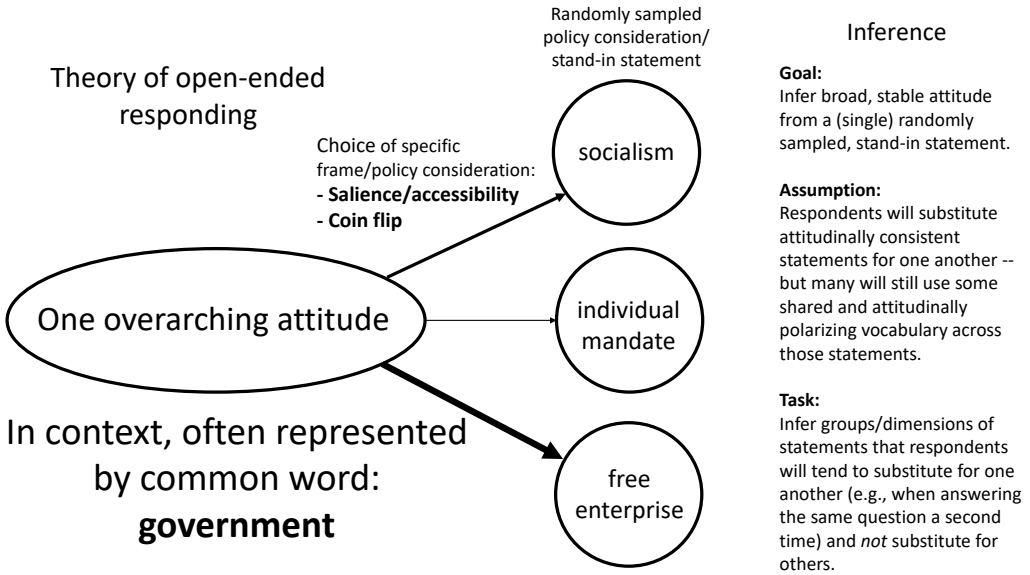


Figure 1: Inferring broad, stable attitudes from respondents' individually sampled, stand-in statements. Vocabulary shared across many statements will become *contextually common*, and some subset will also be attitudinally polarizing. We argue that we can use these words to infer broad, stable attitudes. In doing so, we discount relationships *among* rare words, but still leverage rare words' corpus-level associations with more contextually common words.

Scoring common words

Our approach to inferring attitudes boils down to calculating a score that measures whether a document is 'about' a contextually common word – whether or not the word was itself used – and then applying dimensionality reduction to summarize covariation in those 'implied word' scores. The goal is to estimate the extent to which one could substitute what the

respondent happened to say with other statements without changing what they meant – and through this, infer what statements a respondent *could have* made consistent with the same general attitude.

Importantly, and in contrast with common practice in many text analysis approaches (e.g., tf-idf weighting), this approach works in part by *discarding* some information – particularly associations *among* rare words – that is *on average* likely to reflect noise rather than signal *with respect to stable attitudes*. As with most common approaches, including topic models and sentiment analyses, our approach produces a list of words and associated scores on a dimension. It differs in attempting to estimate dimensions and word scores that better reflect stable responses and the underlying attitudes that produced them. Although we develop this theory and method with the English language in mind (and our tests are limited to the US political context), we believe that it can be readily extended, with appropriate validation, to other languages and applied to non-US contexts.[4]

We begin with a fully in-sample method to illustrate our broader points about measurement error and the context-specific and symbolic meanings of common words. We then in Section 5 demonstrate how it can be augmented with pre-trained embeddings to improve both performance and interpretability. It is likely that large language models will eventually outperform methods that rely on in-sample data. However, at present, large language models *on their own* are unlikely to account for symbolic uses of words that are relatively common across respondents in a fully unsupervised setting – without the researcher providing relevant context and guidance. To maintain our substantive focus, full details of this method are included in the SI (Appendix Section B.6, which is an unabridged version of this text;

[4]The method's performance may depend more heavily on pre-processing steps to convert responses to a document-term matrix for some languages (e.g., word segmentation algorithms for Chinese), and the performance of extensions using large language models in other languages may depend on the quality of the training data for those models.

and Appendix Section C, which is an explanation with annotated R code).

We compare a document-term matrix to a matrix that stands in for the respondent sampling distribution (the range of considerations to sample from) when a document is about an implied word. That matrix contains conditional distributions of co-ocurring words in all responses to the same or closely related prompts – i.e., across documents that contain the word 'people', what fraction of (unique) words in those documents was the word x.

To compare documents' stated words to the implied words' sampling distributions, we use Bhattacharyya coefficients (which measure overlap in probability distributions) for every word in the corpus. Regardless of whether a document uses the word "people", we still calculate whether the distribution of words in the document resembles the distribution of words for all other documents in the corpus that did use the word "people."

Concretely, for a document i, stated word(s) j, and implied word k, the following calculation produces a document similarity score for word k in document i (a word that the document might be 'about'):

$$m_{ik} = BC(d_i, g_k)_{ik} = \sum_{j=1}^{p} \sqrt{\frac{d_{ij}}{\sum_{j=1}^{p}(d_{ij})}} \sqrt{\frac{g_{jk}}{\sum_{j=1}^{p}(g_{jk})}}$$

where d_{ij} is an element in the original document-term matrix (whether word j was used in document i), g_{jk} is an element in the corpus conditional word co-occurrence matrix (approximately: of respondents who used the word k, the fraction who also used the word j), and m_{ik} an element in the transformed document-term matrix (whether document i appears to be 'about' word k).

Below, we illustrate this process for a document that states: "they spend too much". We compare this document to the conditional distributions of common words in the corpus, using the words people, issues, beliefs, candidates, help, and waste as these words (in our later analyses, we exclude stop words like 'they' and 'the'). This calculation shows that,

although this document does not explicitly use the word waste, the method identifies waste as the most likely 'topic' of the sentence.

$$\sqrt{\frac{d_{ij}}{\Sigma_{j=1}^{p}(d_{ij})}} = \begin{array}{c} \begin{matrix} \textit{they} & \textit{spend} & \textit{too} & \textit{much} \end{matrix} \\ \begin{bmatrix} 0.5 & 0.5 & 0.5 & 0.5 \end{bmatrix} \end{array}$$

$$\sqrt{\frac{g_{jk}}{\Sigma_{j=1}^{p}(g_{jk})}} = \begin{array}{c} j's \downarrow \; k's \rightarrow \\ \textit{they} \\ \textit{spend} \\ \textit{too} \\ \textit{much} \end{array} \begin{array}{c} \begin{matrix} \textit{people} & \textit{issues} & \textit{beliefs} & \textit{candidates} & \textit{help} & \textit{waste} \end{matrix} \\ \begin{bmatrix} 0.17 & 0.16 & 0.15 & 0.16 & 0.18 & 0.16 \\ 0.03 & 0.03 & 0.02 & 0.02 & 0.03 & 0.08 \\ 0.06 & 0.08 & 0.05 & 0.07 & 0.06 & 0.11 \\ 0.06 & 0.06 & 0.06 & 0.07 & 0.06 & 0.11 \end{bmatrix} \end{array}$$

$$\begin{array}{l} \\ \textbf{\textit{they spend too much}} \\ \textit{they represent the middle class} \\ \textit{their stance on abortion} \end{array} \begin{array}{c} \begin{matrix} \textit{people} & \textit{issues} & \textit{beliefs} & \textit{candidates} & \textit{help} & \textit{waste} \end{matrix} \\ \begin{bmatrix} 0.16 & 0.16 & 0.14 & 0.16 & 0.17 & \mathbf{0.23} \\ \mathbf{0.23} & 0.19 & 0.18 & 0.18 & \mathbf{0.24} & 0.17 \\ 0.11 & \mathbf{0.19} & \mathbf{0.18} & 0.14 & 0.10 & 0.12 \end{bmatrix} \end{array}$$

Table 1: We illustrate calculations for the transformed document-term matrix. Each row of the transformed matrix is standardized (see text) prior to singular value decomposition. The leading dimension of this method will capture the number of words and use of more common words across documents, and the next will be the first substantive dimension.

Importantly, this approach will more heavily weight common words than rare words and do so across *all* of the comparisons (see SI Figure B.2)

To better understand the broad associations of different common words across a corpus, we need to use some form of dimensionality reduction. We use singular value decomposition. Because this captures dominant sources of variation in the data, the singular vectors from this provide the top candidate dimensions that could represent (polarization in) attitudes (after the leading dimension, which captures overall prevalence).

Prior to applying SVD, we standardize the data, weight training data so that each survey wave is treated equally (in the ANES, recent waves are far larger with added online samples),

and run SVD only on the q most common words in the corpus. For our analyses below, we restrict q to the number of words whose squared frequency is greater than the average squared frequency. We show in the appendix that we see the same results for word frequencies simply greater than the average frequency. However, with that setting, the dimensions are sometimes highly correlated with each other, which could exaggerate the reliability of the findings.

Resulting word scores are $G^\top V$. Document scores are produced from the matrix multiplication $D(G^\top V)$ and then standardized so that each observation has a Euclidean norm of one. In this, D represents the document-term matrix, G the standardized word co-occurrence matrix/sampling distribution matrix (truncated to all words' co-occurrences with common words – so that, after the multiplication $G^\top V$, we are able to score uncommon words in our document-term matrix), and V the right singular vectors of singular value decomposition of M, the transformed document-term/'implied word' matrix. We illustrate this process with (working) R code in SI Section C.

When listing keywords, we multiply word scores by the square root of words' frequencies and then report the top words with the largest values on each side of the scale. This multiplication ensures that the keywords reflect the influence of common words on the scaling process, as illustrated in Figure B.2 – we treat common and rare words equally when assigning *document* scores.

Scoring common words with large language models?

It is possible to create a version of the transformed document-term matrix we described in the previous section – whether a document is 'about' a common word – using large language model based zero-shot classification. We evaluate the out-of-the-box performance of zero-shot classification by classifying whether a text is 'about' the top 1,000 words in each corpus. For this, we use the BART language model (Lewis et al. 2020) fine-tuned on

the MNLI corpus, as described in Yin et al. (2019) and implemented in the python package 'ktrain' (Maiya 2022).[5] To match the numbering of the implied word method, we label principal components starting at 0 – across these methods, the dimension with the largest variance typically captures some form of prevalence. In the SI, we show that using PCA on the last layer of BERT sentence embeddings (Devlin et al. 2018) performs notably worse than zero-shot classification for this purpose.

In the SI, we contrast the common word approach with an approach that emphasizes 'response distinctiveness', meaning responses categorized by how different they seem compared to other responses in a corpus.

Topic model comparison

We compare our method to topic models across many settings of k (the number of topics), since many topic model users will try multiple specifications before settling on a preferred model and, unlike our scaling method, topics are unordered. With this output, we assess the fraction of topics that match the performance of the implied word method on test-retest reliability and hand label correspondence, as well as the extent to which a topic's correlation with the top dimension of our implied word method predicts the topic's performance. This evaluates whether topic models tend to produce more unstable outputs than stable ones, and whether our method can be used to improve the selection of more stable topics.

[5]Using ChatGPT to produce the 96 million total annotations in this way would currently be prohibitively expensive. While it was possible to drastically reduce the cost by returning multiple labels for multiple responses at once (Mellon et al. 2022) and sampling documents, we found that ChatGPT returned labels that were far too narrow (e.g., only a handful of related terms out of hundreds for each document, even when using model log probabilities). We abandoned this effort when we found that the latest generation of embeddings, also from OpenAI, worked much more reliably.

Hand label comparison

If more frequently-used words (for a given prompt) are likelier to reflect the directional thrust of an attitude, text labels corresponding with those words should also be more likely than labels for less-frequent words to be attitude-like. If a hand labeling codebook is iteratively expanded to include more infrequent and narrow statements, which we argue are often randomly selected by respondents to convey a broader directional thrust, this expansion is unlikely to reflect attitudes. Given this, we assess whether common labels are relatively strongly correlated over time than more rare and fine-grained ones.

Supervised comparison

To contextualize our results, we compare test-retest reliability and associations with hand labels for the unsupervised method outputs described above with supervised text classifiers. These supervised benchmarks are trained on closed-ended ACA favorability (for the ACA attitudes analyses) and partisanship (for the ANES analyses). For these models, we use a ridge regression on document-term matrices, with lambda selected by cross-validation using the 'glmnet' package in R (Friedman et al. 2021).

Using embeddings to describe dimensions and add rare words back in

After we use common words to identify stable attitudes overall, we can then use recently-developed embeddings to better score individual documents (e.g., more accurately placing uses of rare words on the identified dimension). See Section 5 for details on how we embed the implied word method.

3 Tests and Data

We have proposed a theory of open-ended survey responses and argued that this theory can help us infer attitudes in open-ended survey data. We present multiple tests of this theory, and further consider whether our approach complements rather than solely duplicates closed-ended responses.

First, we compare within-subject response stability over time for common words and the top dimensions of our implied word method to that of rare words and topics. This evaluates whether we have succeeded in identifying broad topics and concepts that respondents will tend to substitute for each other because they are consistent with the same underlying attitude.

Second, we assess whether automated methods that perform well on response stability also capture the political topics chosen by survey administrators, as labeled by human coders. This test, in addition to our analysis connecting our results to past literature, is intended to rule out the possibility that unsupervised outputs that are highly correlated over time merely reflect communication style rather than variation in political content. Qualitative labels were presumably considered politically relevant, potentially important, and not merely a reflection of communication style. In this, we evaluate whether there is an organization of these labels that predict common words' directional thrust, rather than attempting to predict them label by label. Relevant to our theory, we have argued that the exact statement will often not reflect underlying and stable attitudes, which we illustrate by assessing test-retest reliability of human-coded labels.

Finally, and connecting the findings to past literature in political science, we demonstrate that our method recovers substantively meaningful variation in responses, even in cases where it does not reproduce a closed-ended stance (such as partisanship). If open-ended responses merely reflected closed-ended responses, there would be little point to including them in

surveys.

After these tests, we provide an additional analysis that combines our approach with embeddings, and also provide techniques and guidance on how to better describe the content of a dimension, more accurately score documents on that dimension, and assess potential problems in the use of the method – including outliers, corpus 'context size', and potential response style effects.

Data

We use three open-ended survey questions from major U.S. surveys for our primary analyses, in addition to social media posts from Twitter for an auxiliary analysis in the SI (Figures D.1 and D.2). These questions are particularly useful for three reasons. First, panel data is available for all of them. Second, most include qualitative hand-labels chosen by the survey administrators. Third, they each appear in a large number of studies over time.

Specifically, these questions are:

- 1) "Could you tell me in your own words what is the main reason you have (a favorable/unfavorable) opinion of the health reform law?" (2009 to 2018 – 14,278 responses)

  For 2009, this question was "What would you say is the main reason you (favor/oppose) the health care proposals being discussed in Congress?"

- 2) "Is there anything in particular that you (like/dislike) about the (Democratic/Republican) party? What is that?" (1984 to 2020 – 62,798 responses)

- 3) "What do you think is the most important problem facing this country today?" (1984 to 2016 – 22,983 responses)

The panel data for the two ANES questions come from the small 1992 to 1996 panel study and the much larger 2016 to 2020 panel study. We also have a large sample for the

open-ended question about the Affordable Care Act – a panel of respondents in the ISCAP study for the 2016 through 2018 period. However, for the ACA panel and the 2016 to 2020 ANES panel, we do not have hand labels. More details on these data sets and coverage years can be found in Section A.2 of the appendix.

From the available ANES data, we excluded most important problem data from 2020. In 2020, many responses mentioned the COVID-19 pandemic, and, because of the uniqueness of those responses (i.e., little overlap in vocabulary with other years) automated methods assign unique dimensions and topics to 2020 content. Meaning, automated methods produce dimensions and topics that capture whether a response comes from the year 2020. We return to this 2020 data in Sections 5 and 6, however, where we explore extensions and limitations of the method, including a means to assess when an open-ended corpus (or other text corpus) may be too broad for our method to work well.

4 Results

Correlation over time

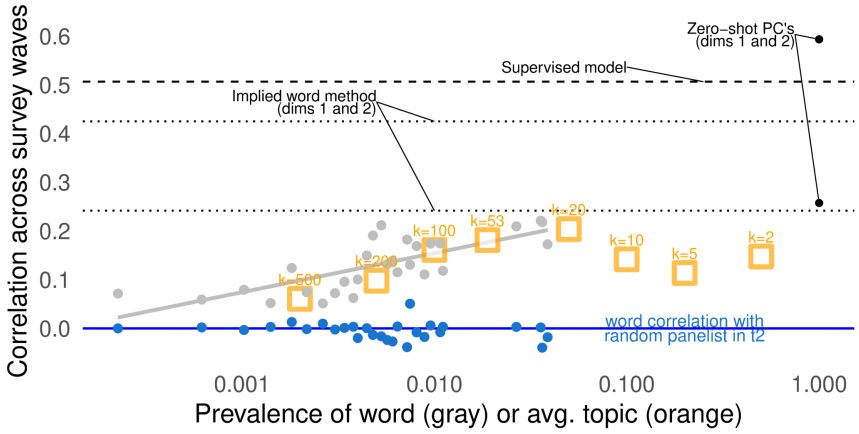
Attitudes reflect general dispositions that people apply repeatedly when thinking about political matters. Our first tests consider the accessibility of common words and the tendency of respondents to re-use common words, above and beyond what we would expect based on their frequencies. We then evaluate whether common human-coded labels and the common-word based dimensions are more strongly correlated over time than less common labels and topics from topic models.

The Affordable Care Act

The left panel of Figure 2 displays correlations across the 2016 and 2018 waves of the ISCAP study. It compares correlations for specific words, topics, and the top dimensions of our

implied word method. We conduct a permutation test (in blue – word correlation with a random panelist in t_2) to show that higher overall frequency does not mechanically produce a stronger correlation.

The figure shows that usage of common words, prevalent topics, and the top dimensions of our implied word method are more strongly correlated across waves than rarer words and less prevalent topics. Further, prevalent topics (averaged here, but separated in SI Section E.1 and in ANES analyses below) are on average as correlated within-user as the most common words.



Implied words		Zero-shot PC's	
people	government	helping	screwed
insurance	much	positive	terrible
health	involved	helps	sucks
everyone	going	beneficial	failure
coverage	cost	helpful	oppose
afford	money	helped	bad
access	everything	good	poorly
conditions	want	help	opposed
helps	control	right	disagree
affordable	run	providing	unfair

Figure 2: *Top:* Correlation in word use, topics, and document scores over time in open-ended survey responses. On average, contextually common words and topics are more correlated than rare words over time. Dotted lines are from unsupervised model dimension correlations. N panelists=1,094. *Bottom:* Keywords from first substantive dimension for co-occurrence based implied word method and zero-shot principal components.

Promisingly, the first substantive dimension from PCA on the zero-shot 'implied word'

matrix out-performs all other approaches in test-retest reliability. However, as shown in the keywords table below in Figure 2, this performance appears to be driven by the zero-shot model's ability to detect sentiment – reflecting generally positive or negative words that we would not expect to vary across political contexts. Recall that this open-ended question followed a closed-ended question regarding favorability toward the ACA. Reproducing this sentiment adds little additional information to the closed-ended response. By contrast, the first dimension that emerges in our approach recovers substantive differences in how respondents think about the Affordable Care Act – spanning concerns about the role of government, on the one hand, and access to affordable health care on the other.

The 'Most Important Problem' and Partisan Likes/Dislikes

We next compare approaches using open-ended responses that are less strongly related to partisanship than the ACA.[6]

Figure 3 displays within-subject correlations in the 1992 to 1996 and 2016 to 2020 ANES panels for a supervised text model, the most frequent human-coded categories ordered by prevalence, the implied word method, zero-shot principal components, and topics from several models with different settings of k (the number of topics). 'Keywords' in the 2016-2020 panel combined multiple search terms – e.g., abortion represents a search for "abortion|prolife|prochoice|pro-choice|pro-life|right to choose|roe." We were able to analyze these keywords in this 2016-2020 analysis because the 2016-2020 panel is much larger than the 1992-1996 panel. There are no hand labels for years 2016 and 2020.

These comparisons illustrate two key points. First, the principal components from zero-shot classification are less reliable than the most prevalent labels and the top dimension of the implied word method. This method appears to discover variation in responses that might be meaningful in more general contexts, but that does not predict re-use across survey

[6]In our data, closed-ended ACA attitudes and partisanship are correlated at about 0.6.

waves. Keyword tables for zero-shot PCA output are in SI Tables E.4 and E.6. Second, the most strongly correlated dimensions from our (unsupervised) implied word method are on par with a supervised text model trained to predict 7 point partisan identification. In the comparison to topics models, a few of the topics perform as well as the implied word method, but they are rare and tend to those most highly correlated with the first dimension of the implied word method.

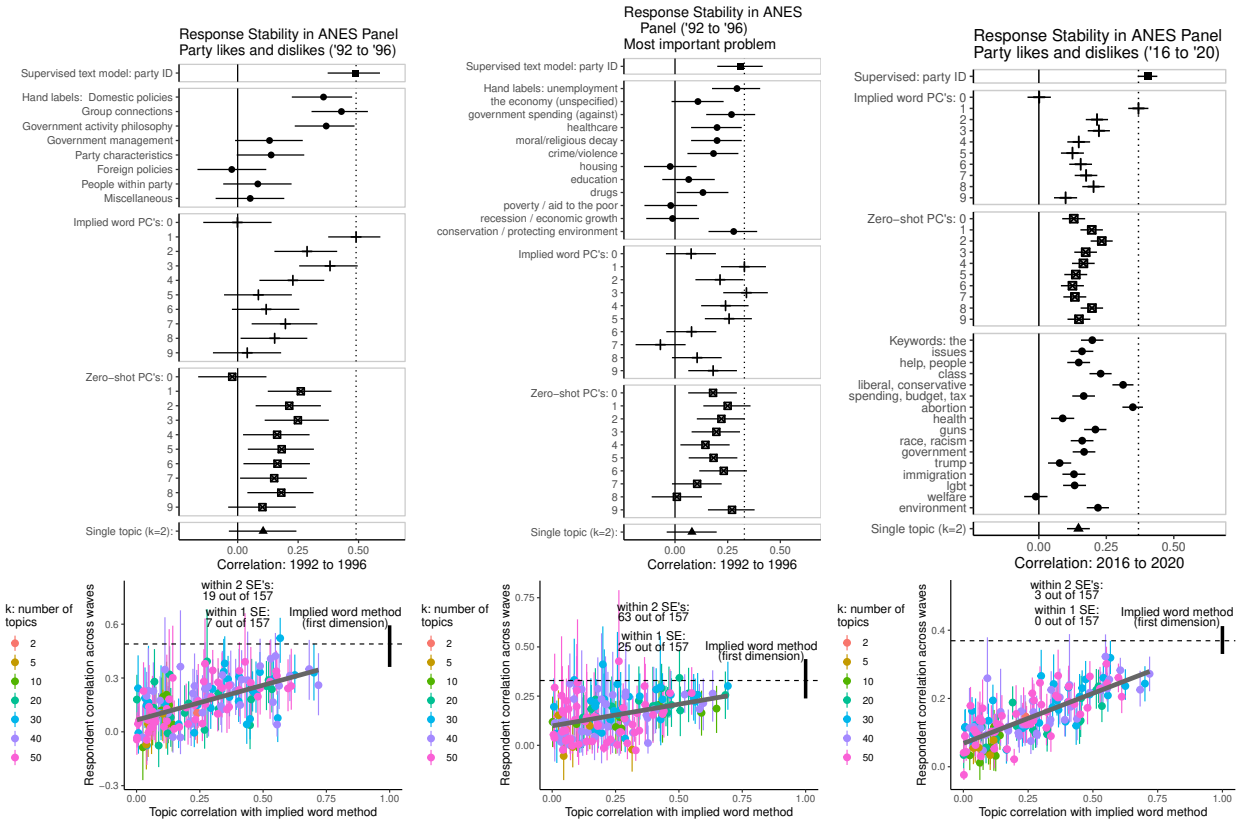


Figure 3: Each measure is ordered by prevalence (hand labels), correlation with the implied word method (topics), or variance explained (automated methods). 1992-1996: N panelists=193 (party likes/dislikes); N panelists=270 (most important problem). 2016-2020: N panelists=2,053 (party likes/dislikes).

In SI Section E.3, we further illustrate our topic model findings using a subset of topics, from a model with 69 topics, that we deemed to be especially coherent. There, again, we show that topics – whether or not they have coherent sets of keywords – are often not very

strongly correlated within-individual over time.

Higher order structure for coding schemes

We next consider associations with human-coded labels of political content. This assesses whether the implied (common) word dimensions and other unsupervised outputs might merely reflect communication style, rather than *both* being highly correlated over time while also reflecting structured variation in substantive political content.

We do not assess whether we can automate the hand labeling of responses. We have already evaluated whether hand labels themselves were highly correlated over time. For those tests, most of the texts were already hand labeled and a perfect supervised method would merely reproduce those labels.

The Affordable Care Act

In Figure E.1 in the appendix, we show that the ACA attitude text dimensions with high test-retest reliability (from both our implied word method and its zero-shot analogue) also correspond with labels assigned by survey administrators. They do not merely reflect writing styles.

The 'Most Important Problem' and Partisan Likes/Dislikes

Figure 4 displays the multiple R (the bootstrapped 95% confidence interval) for each dimension of each measure studied in the test-retest analysis. This assesses whether we can predict the automated measure using the human-coded labels, restricted to labels that appear at least 10 times and over 8 waves (leaving the remaining labels as a reference group). We consider whether the combination of human-coded labels is likely to be politically meaningful in the next section.

This figure shows that, again, the top dimensions produced by the implied word method tend to be strongly correlated with the human-coded labels, and at a level on par with a supervised model using the text to predict party identification. Similar to the test-retest analysis, some topics also carry relatively strong associations with the human-coded labels, although this pattern is less consistent and tends to appear for topics more strongly correlated with the first dimension of the implied word method.

We supplement these tests ruling out mere communication style effects in Section 6.

Novelty, Correspondence with Political Science Theory, and Political Context

We now turn to the question of whether dimensions of the method that are correlated over time and that can be predicted by human-coded labels are a) politically meaningful and b) 'novel'.

In Table 5, we show the associations between the first dimension and the non-collapsed ANES human-coded labels of the likes and dislikes open-ended responses. The first dimension reflects issue-based versus group-based justifications for party likes and dislikes. These labels are from the same analysis as in Figure 4, where the dependent variable was the text measure and the independent variable was an indicator representing each label. These are ordered by the value of their regression coefficients.

This is notable because it closely corresponds with the higher "levels of conceptualization" Converse (1964) identified in qualitative interviews with members of the mass public regarding the bases on which they evaluated political objects. In analyzing these interviews, Converse differentiated "ideologues" and "near-ideologues" who referenced abstract concepts along the liberal-conservative spectrum when articulating their likes and dislikes of parties and candidates from those who evaluated these objects with respect to particular social

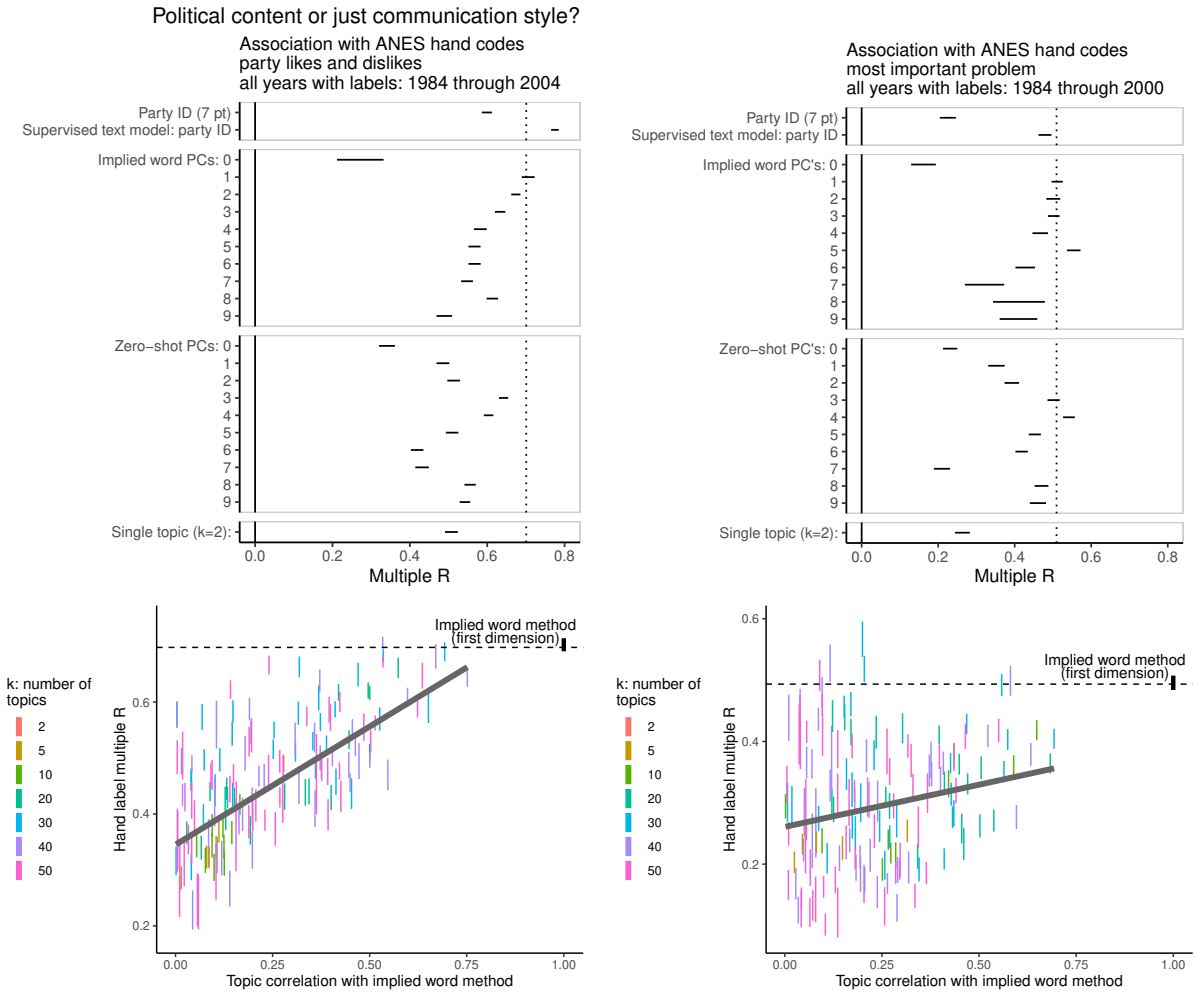
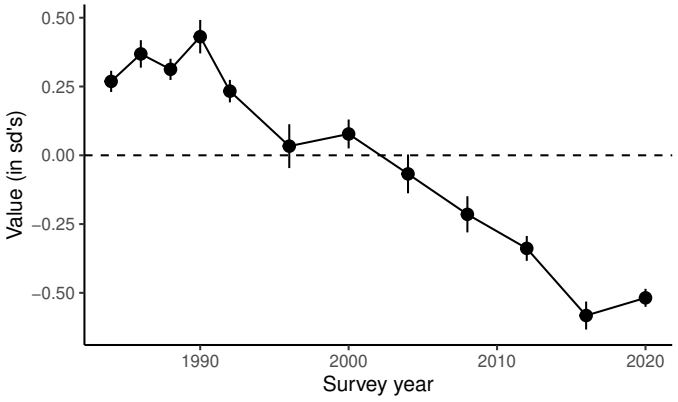


Figure 4: Do more prevalent topics and the top implied word dimensions merely reflect communication style? Or do they reflect variation in politically meaningful content? This analysis tests correspondence between automated methods and combinations of ANES hand labels for categories of *political* content – multiple R (bootstrapped 95% confidence interval) for each dimension of each measure studied in the test-retest analysis. In each regression, the dependent variable is the automated text analysis output and dependent variables are dummies for hand labels. N respondents=8,787 (party likes/dislikes, 1984-2004); N respondents=11,776 (most important problem, 1984-2000). Figure E.5 further shows strong associations between issue preferences and the top implied word dimension, with divergence from party-line stances on social versus economic issues.

groups. Here, the first dimension of the likes and dislikes differentiates respondents who reference policy issues with clear ideological valence (abortion, gun control, immigration, e.g.) and ideological concepts themselves (conservative) from those who reference more general

1st dimension keywords

abortion	people
rights	rich
stance	poor
gun	class
pro	working
views	get
issues	help
conservative	always
marriage	man
gay	middle
immigration	money
values	just
control	office
womens	know
stand	think



1st dimension hand labels

Issues/positions/ideology	Groups/performance/candidates
Abortion and birth control (unk. direction)	Common/little/working people (pro)
Abortion and birth control (anti: reform/legalization)	Poor people / needy (pro)
Abortion and birth control (pro: reform/legalization)	Just a democrat / couldn't vote republican
Too conservative	Big business, the rich (pro)
General assessment of ideas policies stances	Income/employment better under them
Gun control (unk. direction)	Can't trust them
Strong military position	White collar workers / middle class
Too liberal	Poor people / needy (anti)
Public morality / defends family values	Ronald Reagan
For government / social programs spending	Campaign tactics / mud slinging
General assessment of economic policy	Can trust them
General assessment of foreign policies / stances	Local party figures
Against government / social programs spending	Look for more qualified / don't pay attention to parties
Socialistic	Wages/salaries/employment worse under them
Favor social change/reform/progress	Aid programs for older people (anti)

Figure 5: Average party likes/dislikes response in the ANES over time – first dimension of the implied word method. More negative is more issue focused and more positive is more group focused. Hand labels are largest magnitude coefficients from the regression analysis in Figure 4. Responses have become more issue focused over time, in line with research on partisan polarization (Webster and Abramowitz 2017) and issue constraint (Hare 2022).

class distinctions and distributive politics (rich, poor, working/middle class, help).

In Figure 5, we show that responses in the ANES have shifted on this dimension over time. Compared to responses from 1984 through 1992, open-ended responses about party likes and dislikes in 2012 through 2020 were far more likely to mention issue-based/ideological likes and dislikes over group (in this data, largely based on income), performance, and candidate-based concerns. This is consistent with work showing increases in issue-based polarization (Webster and Abramowitz 2017) and issue constraint (Hare 2022) over this time period, and extends these findings to suggest that a greater share of citizens are evaluating political

parties and candidates in ideological terms.

5 Using LLM's to better describe dimensions and score documents

Our 'implied word' method identifies dimensions in text that tend to be highly correlated over time – consistent with a method that identifies topics/concepts that can be substituted for each other in an attitudinally consistent way. However, without pre-existing hand labels, it may be challenging to efficiently describe the contents of a dimension to the reader of an article who may not have access to many of the texts to read themselves, since our method relies on context-specific and potentially symbolic meanings of words.

Given this problem, we developed a generative AI and embedding technique for generating more descriptive labels for dimensions. We use generative AI to produce labels for each document in our corpus, prompting ChatGPT 3.5 (through an institutional account on the Microsoft Azure platform, which provides greater data privacy assurances than OpenAI's platform) to provide a few topical categories for each open-ended response (see SI Section H.1 for prompt). From there, we used OpenAI's v3 large embeddings (through Azure), which they released in January 2024 (during review of this paper), to embed each of those topical categories – submitting each open-ended response and a prompt (see SI Section H.2 for prompt) to the embedding API for a document-level embedding.

To embed the open-ended responses on our implied word dimension, we multiply the centered document implied word scores by the document embeddings and then average the embeddings (i.e., an average for each 3,072 embedding dimensions) across all documents for an embedded version of our implied word scores. We then calculate the cosine similarity for each category embedding and the implied word embedding vector. The labels for each dimension are then those with the top 100 most positive and most negative cosine similarities.

We provide R code to reproduce this process at the end of our code walk-through in Section C of the SI.

We illustrate these categories for the first dimension of the party likes and dislikes data in the top panels of Figure 6. These are consistent with hand labels, though with more labels differing on social versus economic dimensions than the hand labels and with less of a candidate focus on the representation side of the output. The candidate focus is prominent in the embedded output again in the 2016 re-analysis described below, as shown in the labels in top panels of SI Figure H.2.

Using embeddings to better score implied words dimensions at the document level

Once we have embedded our implied word dimension, it is straightforward to then ask whether this embedded version has the same or better performance than the original. This matters because we change the meaning of a dimension somewhat after this embedding process, but we are likely to have more accurately scored documents on the implied word dimensions (i.e., our method focuses on finding a reliable dimension in aggregate, but may exhibit high variance at the document-level). With the implied word embedding described above, we then score each document on that embedded dimension by calculating each document embedding's cosine similarity with the implied word embedding (a separate embedding for each dimension of the implied word method output – though we focus in the main text on dimension 1).

We test this in Figure 7, where we find equal or improved performance for the latest generation embeddings (and much poorer performance for the older generation, represented by BERT). Further, when the embedding process is successful, PCA on those embeddings tends to perform relatively well – and not very far below the performance of the *embedded*

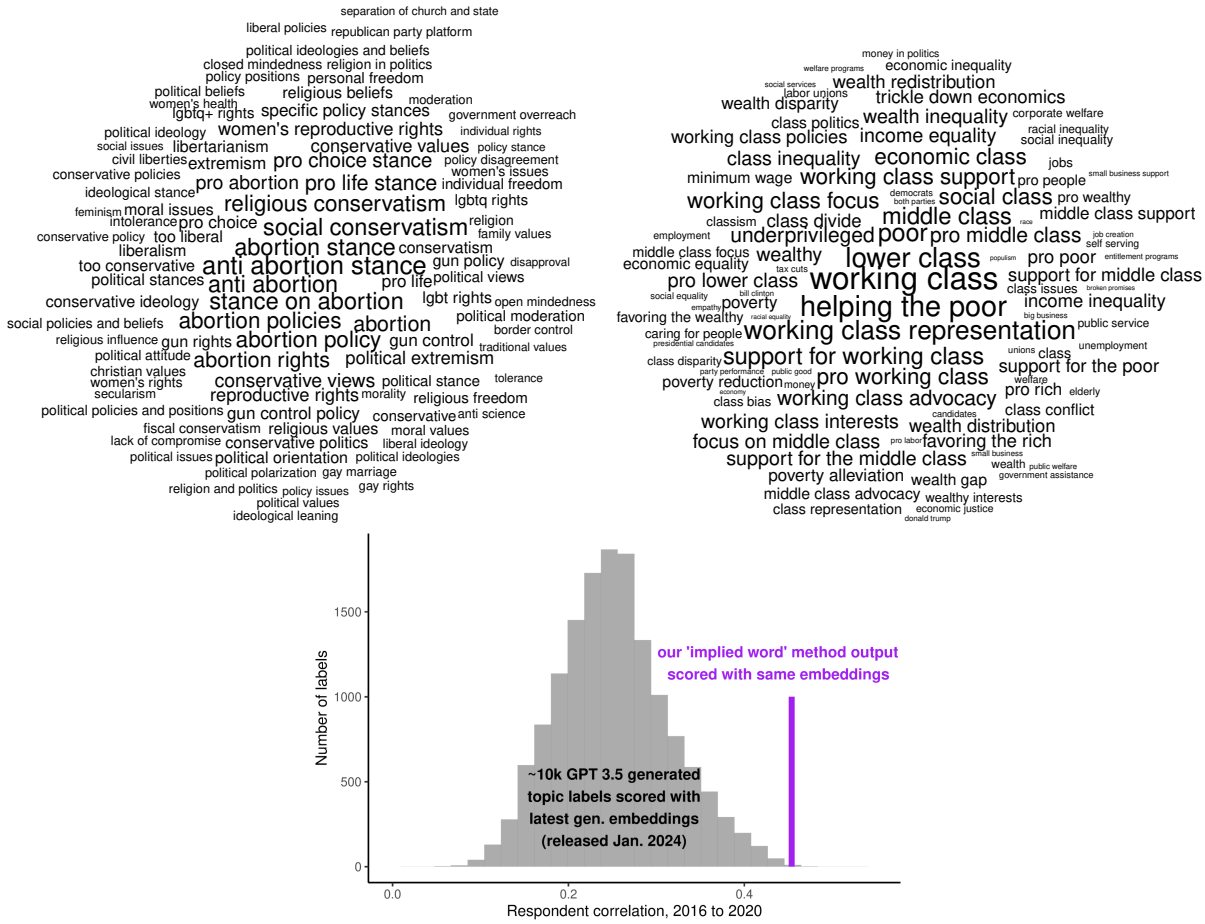


Figure 6: The top panels of this figure display the topic labels with the largest positive and negative cosine similarities for the embedding of our implied word method's first dimension, sized by relative cosine similarity. These labels are useful because our method relies on context-specific and potentially symbolic meanings of words, and lists of those words can be difficult to interpret in isolation. The bottom panel of this figure displays 2016-2020 respondent correlations for scores of approximately 10,000 topic labels generated by GPT 3.5 on the party likes and dislikes data, and the corresponding correlation for the embedded version of our method. Because these labels' *embedding* scores are not stochastic, lower correlations reflect changes in the respondents' answers across waves.

implied word method in terms of test-retest reliability. Unfortunately, we cannot verify that these embeddings will work well across all contexts, however – and this may be difficult to assess ahead of time, since training data details are not public for these models, even to our knowledge the latest generation of 'open-source' models. We suspect that the data sets we analyze here, or online conversations closely related to them, are now relatively likely to be

included in LLM training data.

For the test in 2020, the most important problem question was challenging to analyze because so many responses mentioned the COVID-19 pandemic. It was excluded from our earlier analyses and training data for the most important problem because of this. However, we discovered that over a shorter 4 year interval (rather than close to 40 years), even with a pandemic, the difference between 2016 (only) and 2020 in terms of common word use (i.e., correlation in square root word frequencies) was no larger than other 4 year periods (bottom panels of Figure 7 – see next section for more discussion of this test). Given this, we retrained our implied word method using just 2016 as training data for both ANES questions. This gave us an extra test for our added, latest generation embedding analyses, and also allowed us to better compare test-retest reliability with cross question test-retest reliability (see below).

6 Evaluating style effects, corpus context size, and outliers

Below, we use the two open-ended questions in the ANES to further assess possible style effects. If our first dimensions represent communication style only, then we might observe strong correlations over time between different questions. Figure 8 shows that high test-retest reliability across our first dimensions applies only to test-retest on the same open-ended question. In the 2016-2020 panel, the second dimension of the most important problem implied word scores is more strongly correlated with the first dimension of the likes/dislikes scores (slightly over 0.1 and higher than the null of 0.02).

This test is not definitive – ideally, we would have a method that would be able to capture shared political content across multiple questions, including these questions. We thank a reviewer for this broad recommendation, although we recognize that completely unrelated questions or a political versus non-political question would be preferable.

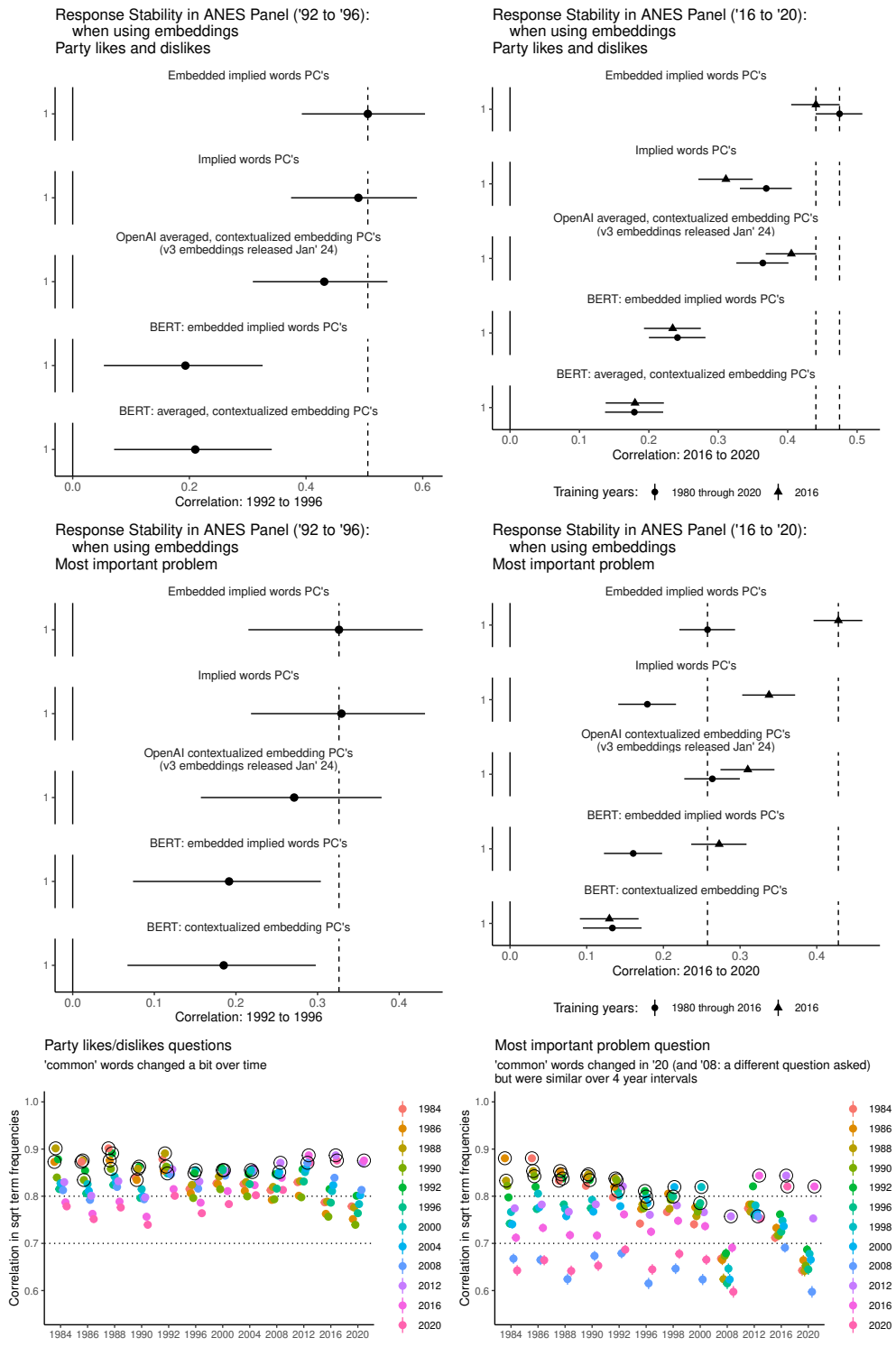


Figure 7: In the top panels of this figure, we display test-retest correlations for the first dimension of our embedded version of our method, along with the first PCA dimension on BERT and OpenAI v3 embeddings (top 10 dimensions and hand label analyses shown in SI Sections H.5 and H.6). In the bottom panel of this figure, correlations in square root word frequencies, and so contextually common words and their associates, diverge in 2020 for the most important problem question, but are still similar to those in 2016. Black circles around the points indicate survey waves that are 4 years or fewer apart.

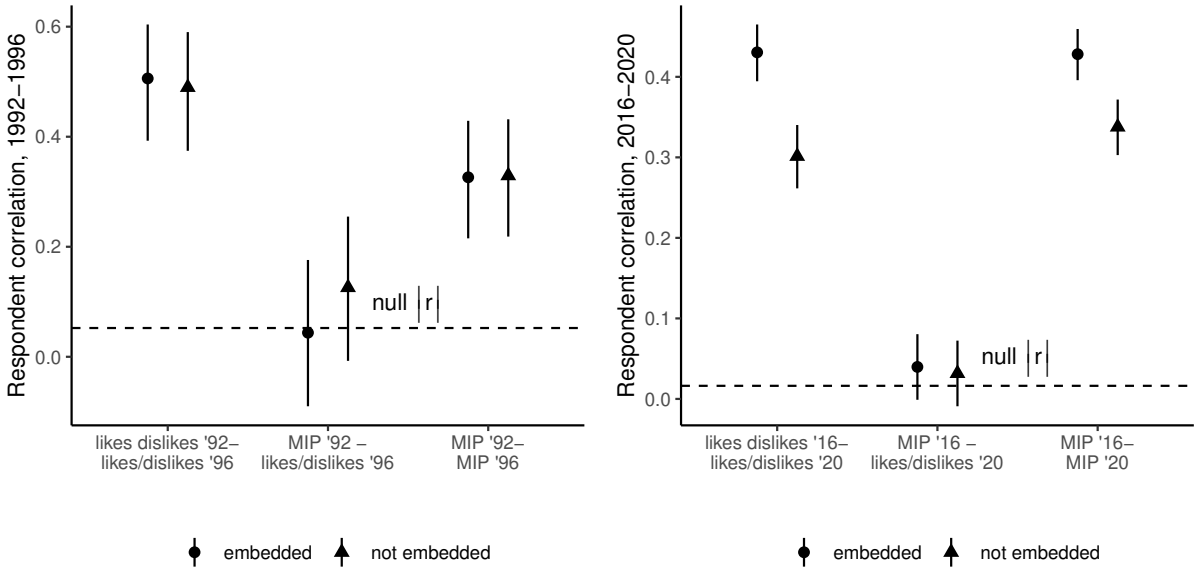


Figure 8: Within-question and cross-question wave-to-wave correlation coefficients. N 1992 post-election most important problem to 1996 pre-election party likes/dislikes: 217. N 2016 post-election most important problem to 2020 pre-election party likes/dislikes: 2306. 2016-2020. Note that the 2016-2020 analysis is based on the implied word method trained on 2016 (see text on 'context window' and pandemic related issues in the most important problem analyses). The dotted line indicates the null value of a normed correlation coefficient (Green et al. 2024).

Next, because the method relies on uses of common words and associations between rare words and common words, we can end up with rare terms that have not been very accurately scored on our dimensions, leading to outliers in the document-level scores. This issue can be corrected by using embeddings (if we are willing to trust the performance of often opaque embeddings) – or we can simply assess potential outliers visually by plotting and looking for outlying observations in word scores and document scores.

Last, the context covered in some corpora may be too large for our method to work well – for example, when what is contextually common for one subset of the data is *not* contextually common for the other. For this, we can split the data on some variable that may drive overly large context size (and a contrast that *we know we do not want the method to identify* – e.g., pandemic versus non-pandemic years) and assess the correlation in word

frequencies across that contrast. We showed this in Figure 7 where, indeed, we find that 2020 is dramatically different from other years in the most important problem data set.

7 Discussion

Advances in natural language processing have made it possible to organize and code open-ended survey responses inexpensively at scale. However, improvements in the speed and accuracy with which researchers can label texts (and in many different ways) are more useful for some tasks than others. These tools can be transformative if and when they allow researchers to tackle more fundamental challenges in measurement.

Toward this goal, we suggest that the key insights of studies on attitudes in closed-ended responses (Converse 1964; Achen 1975; Zaller 1992; Ansolabehere et al. 2008) should be applied to the study of open-ended responses. Respondents have many different, narrow ways to express a broad attitude regarding a specific prompt. This being the case, the ability to efficiently categorize what was said in a single document – i.e. the task for which off-the-shelf large language models are extremely useful at present – is not the same thing as capturing the underlying attitude that document is expressing (and that a respondent is likely to express again), which is often what researchers are more interested in doing.

However, we argue that this task is not wholly intractable. Despite randomness in parts of their answers, if respondents start with a directional thrust, we still expect them to choose some words that reflect more generalizable meaning. This has two key implications for future work concerning attitudes in short text documents such as open-ended survey responses. First, observing how multiple respondents respond to the same prompt is important for capturing the symbolic elements of language that can be used to communicate attitudes. Second, contextually common words (and, more abstractly, common concepts used when responding to a prompt) will be more useful than rare words for inferring distributions of

attitudes.

Our tests support this argument. Contextually common words and text dimensions summarizing variation in how much texts are (symbolically) "about" common words show high within-subject correlation over time and can be predicted by human-labeled categories. Without fine-tuning to better capture the symbolic meanings of words in *local* (i.e. in-sample) context, the output of large language models is less informative of attitudes – even for dimensions of such output that capture a large amount of *between*-subject variation. In contrast, the output from our implied word method – which can then be *augmented* with pre-trained embeddings – efficiently accomplishes this unsupervised inferential task, reproducing findings (such as Converse's "levels of conceptualization") that would otherwise require labor-intensive qualitative analyses of open-ended responses, and would be difficult to elicit in either a closed-ended setting or by using standard topic modeling approaches.

Reducing the costs (in both time and financial expense) of analyzing open-ended responses is important given their usefulness for understanding political attitudes. In studying attitudes, we are interested in understanding how some attitude object, like an issue or party, is represented in the mind of a respondent. Issues and parties change over time, both in terms of their content and members but also in what they represent to the public. If we use only closed-ended questions to ask about them, then the same responses, especially at different time points, can mean very different things. The Democratic and Republican parties in the 1980's had different platforms and priorities than they do today – and someone who voted for a party then was voting for a different type of representation than they are now. Open-ended questions allow us to extract evaluations of attitude objects that are broader than closed-ended ones in the sense that we can understand both whether a person supports or opposes an issue or party and also what that issue or party means to them.

Open-ended responses are also useful relative to other forms of free form text because, in principle, studying attitudes in the open-ended survey setting should be much more straight-

forward than in general text. The open-ended question prompt provides a common attitude object for respondents to evaluate. Without a prompt to focus responses, we would need to first identify an attitude object (whatever someone chooses to discuss and evaluate in a document) and *then* attempt to infer their corresponding attitude. Even beyond that, there can be substantial selection bias in who *chooses* to publicly articulate their political views (e.g., on social media), including why they like or dislike a political party.

A primary recommendation for developing qualitative codebooks is that researchers should read either all or a relatively large, random sample of the texts to better understand the in-context associations of common words. And, although crowd-sourced ratings of topic/keyword cluster quality based on the (potentially out-of-context) semantic coherence of cluster keywords (Ying et al. 2022) can be helpful, coherence ratings can still be unrelated to the usefulness of a topic *as a measure of a stable attitude*. Similarly because of *respondent-driven* measurement error that can lead to high coherence without high response stability, we suggest striking a balance between inter-rater reliability and observed or anticipated test-retest reliability.

Last, we cannot over-emphasize the importance of high-quality data – especially panel data. More panel data will be needed to further advance our understanding of open-ended survey responses, and panel data built on probability samples is usually extremely expensive. The need to ensure that written responses are not produced by AI only increases their cost. We hope that the framework provided here can help justify that expense.

8 Funding

Data collection for the ISCAP panel was supported by the Russell Sage Foundation (awards 94-17-01 and 94-18-07 – PI Hopkins, co-PI Hobbs).

9 Data Availability Statement

Code and data to reproduce the findings in this paper are available at `https://codeocean.com/capsule/1205164`, and an R package to implement the 'implied word' method is available at `https://github.com/wilryh/impliedWords`. KFF data can be downloaded from the Roper Center's iPoll database (`https://ropercenter.cornell.edu/ipoll`), and The Pew Research Center surveys from `http://www.pewresearch.org/data/download-datasets/`. ANES data can be downloaded from `https://www.icpsr.umich.edu/web/pages/`. ISCAP panel data can be downloaded from `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/CYISG1`. The social media data used in SI analyses (Figures D.1 and D.2) is publicly viewable but, due to new API access restrictions, the text of shareable tweet ID's can no longer be downloaded in bulk through Twitter's academic API. We will release highly aggregated Twitter text data with the replication materials.

10 Competing Interests

The authors have no competing interests to report.

11 Research with Human Subjects

Data collection for the ISCAP panel was evaluated by the Cornell University IRB (protocol 1809008257, exempt).

12 Acknowledgments

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Supporting information for:

"Categorizing topics versus inferring attitudes: a theory and method for analyzing open-ended survey responses"

William Hobbs and Jon Green

Table of Contents

A Data

A.1 Text pre-processing

- Probes removed (e.g., the interviewer writing down that they asked "anything else?") and terms with 2 or fewer characters removed (the default 'stm' package setting – this ensures that the two-letter probes are removed)
- Names of presidents and presidential candidates removed (most important problem responses)
- Non-English language responses were removed
- All most important problem mentions were combined into a single text response (for years where mentions were asked and/or recorded separately), since they all came from the same prompt and we were unable to cleanly split responses in years containing first/second/third answers in one
- All party likes/dislikes were analyzed together (e.g., dimensionality reduction methods were run on both likes and dislikes) and then averaged, since they had slightly different prompts
- Automated standardization with "stm" package (lowercase, snowball stopwords removed, including stopwords written without apostrophes)
- Training/test splits for the ACA attitudes analysis (KFF and Pew responses formed the training sets and ISCAP panel responses were not included in training)
- Panel responses from the ANES are included in overall training (but not the 2016 only training added later): to simplify the 3 analyses in the main paper – test-retest, hand label correspondence, over time changes – each of which might justifiably have different training-test splits
- ANES years are equally weighted using survey weights (i.e., the much larger 2016 wave, which includes a large online sample, does not count more than earlier waves with only face-to-face data), with the exception of the topic models (as the 'stm' software, to our knowledge, does not allow use of weights in training)

A.2 Questions and samples

A.2.1 "Could you tell me in your own words what is the main reason you have (a favorable/unfavorable) opinion of the health reform law?"

2009 question (Pew): "What would you say is the main reason you (favor/oppose) the health care proposals being discussed in Congress?"
Hand labels: from the Kaiser Family Foundation surveys (2010-2015).

Years:	2009 (Pew) 2010-2015 (KFF) Jan '16, Oct '16, and Oct '18 (ISCAP)
Number of responses:	14,278
Number of hand labeled responses:	11,094
Panel responses:	2,770
Panel respondents:	1,094

Table A.1: ACA attitudes open-ended response sample sizes.

A.2.2 "Is there anything in particular that you (like/dislike) about the (Democratic/Republican) party? What is that?"

Hand labels: 1984 - 2004 (every two years 1984-1992, every four years 1996-2004).

Included years:	1984 - 2004 (every two years 1984-1992) 2008 - 2020
Excluded years:	none
Number of responses:	62,798
Number of hand labeled responses:	21,850
Panel responses: **Panel responses:**	514 (1992-1996, 1-4 per respondent), 5,543 (2016-2020)
Panel respondents:	193 (1992 to 1996); 2,053 (2016 to 2020)

Table A.2: Party likes/dislikes open-ended response sample sizes.

A.2.3 "What do you think is the most important problem facing this country today?"

Hand labels: 1984 - 2000 (every two years, other than 1994).

Included years:	1984, 1986, 1988, 1990, 1992, 1996, 1998, 2000, 2004, 2008, 2012, 2016
Excluded year(s):	2020 (pandemic)
Number of responses:	22,983 (and 7,214 in 2020)
Number of hand labeled responses:	11,776
Panel responses:	540 ('92-'96), 5,072 ('16-'20)
Panel respondents:	270 ('92-'96), 2,536 ('16-'20)

Table A.3: Most important problem open-ended response sample sizes.

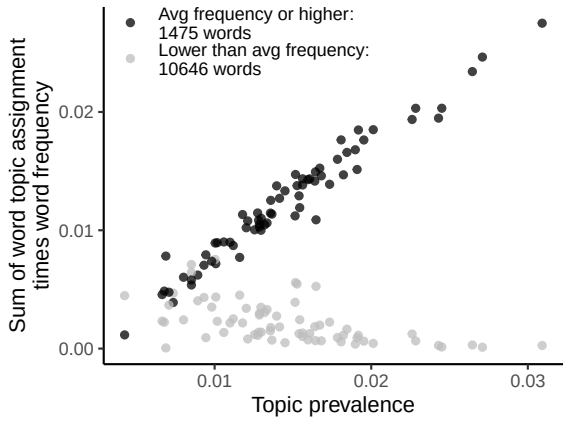


Figure B.1: This figure shows the contributions of common and rare words to topic prevalence in a topic model on the party likes and dislikes data (with k selected automatically using (Mimno and Lee 2014) as implemented in stm (Roberts et al. 2016)). Common words (here, those appearing more frequently than average) determine the prevalence – the frequency of more rare words is not associated with prevalence.

B Methods details

B.1 Topic models

- Uses "stm" package (Roberts et al. 2016)
- stm without covariates (a correlated topic model)
- $k = 2$, 5, 10, 20, 30, 40, 50 (in main paper)

In Figure B.1, we show that topic prevalence is strongly correlated with having a small number of frequent words in a topic.

B.2 Zero-shot labels and PCA

- Zero-shot classification of "This text is about ___."
- Uses the BART language model (Lewis et al. 2020) fine-tuned on the MNLI corpus, as described in Yin et al. (2019) and implemented in the python package 'ktrain' (Maiya 2022).
- Labels were the top 1,000 words in the corpus
- Like the implied word method, PCA on matrix of square roots of probabilities

B.3 BERT embeddings and PCA

We observe no meaningful difference when using BERT embeddings in place of zero-shot classifications, and so these findings are not included in the main paper (they are retained only in SI figures).

- PCA on last layer of BERT sentence embeddings

B.4 Response distinctiveness

- BERT last layer sentence embeddings
- average embedding location for documents that contain a given word versus documents that do not
- response distinctiveness is the Euclidean distance between the contains word and does not contain word location averages
- these calculations and distances mirror embedding regression in Rodriguez et al. (2023), but where differences were instead calculated across groups for documents containing the same word

B.5 Supervised models

- trained on closed-ended ACA favorability (for the ACA attitudes analyses – favorable or not favorable) and trained on partisanship (for the ANES analyses – 7 point scale).
- ridge regression on document-term matrices, with lambda selected by cross-validation (as implemented in the R package 'glmnet' (Friedman et al. 2021))

B.6 Implied word method

This section present an unabridged version of the implied word method explanation contained in the main text, repeating text included there so that a reader does not have to go back and forth between the two.

Overall, the implied word method calculates a score that measures whether a document is 'about' a common word – whether or not the word was itself used – and then applying dimensionality reduction to summarize covariation in those 'implied word' scores. The goal is to estimate the extent to which one could substitute what the respondent happened to say with other statements without changing what they meant – and through this, infer what statements a respondent could have made consistent with the same general attitude.

More specifically, we compare a document-term matrix to a matrix that stands in for the respondent sampling distribution (the range of considerations to sample from) when a document is about an implied word. That matrix contains conditional distributions of co-ocurring words in all responses to the same or closely related prompt – i.e., across

documents that contain the word 'people', what fraction of (unique) words in those documents was the word x.

To compare documents' stated words to the implied words' sampling distributions, we use Bhattacharyya coefficients, which measure overlap in probability distributions. We do so for every word in the corpus. That is, whether or not a document uses the word "people", we still calculate whether the distribution of words in the document resembles the distribution of words for all other documents in the corpus that did use the word "people".

Concretely, for a document i, stated word(s) j, and implied word k, the following calculation produces a document similarity score for word k in document i (a word that the document might be 'about'):

$$m_{ik} = BC(d_i, g_k)_{ik} = \sum_{j=1}^{p} \sqrt{\frac{d_{ij}}{\sum_{j=1}^{p}(d_{ij})}} \sqrt{\frac{g_{jk}}{\sum_{j=1}^{p}(g_{jk})}}$$

where d_{ij} is an element in the original document-term matrix (whether word j was used in document i), g_{jk} is an element in the corpus conditional word co-occurrence matrix (approximately[7]: of respondents who used the word k, the fraction who also used the word j), and m_{ik} an element in the transformed document-term matrix (whether document i appears to be 'about' word k).

Below, we illustrate this process for a document that states: "they spend too much". We compare this document to the conditional distributions of common words in the corpus, using the words people, issues, beliefs, candidates, help, and waste as these words (in our later analyses, we exclude stop words like 'they' and 'the'). This calculation shows that, although this document does not explicitly use the word waste, the method identifies waste as the most likely 'topic' of the sentence.

Importantly, this approach will more heavily weight common words than rare words and do so across *all* of the comparisons. In the conditional distribution matrix, although each column is normalized to sum to 1, the rows are still strongly associated with word frequency.[8] To confirm the strong weighting toward frequent words, we illustrate in Figure B.2 that vectors for common words are more strongly correlated across the Bhattacharyya coefficient matrix and the original document-term matrix than more rare words.

This approach is not enough on its own to study attitudes. To better understand the broad associations of different common words across a corpus, we need to use some form of dimensionality reduction. This will provide a set of words that may be more recognizably symbolic as a group, *and* that more strongly vary across respondents.

We use singular value decomposition for that dimensionality reduction. Because this captures dominant sources of variation in the data, the singular vectors from this provide

[7]We do not zero out the diagonal of the word co-occurrence matrix. More precisely: across documents that contain the word 'people', what fraction of (unique) words in those documents was the word j.

[8]Note that the example table does not sum to 1 because it is a subset of the full matrix.

$$\sqrt{\frac{d_{ij}}{\Sigma_{j=1}^{p}(d_{ij})}} = \begin{array}{c} \begin{matrix} \textit{they} & \textit{spend} & \textit{too} & \textit{much} \end{matrix} \\ \begin{bmatrix} 0.5 & 0.5 & 0.5 & 0.5 \end{bmatrix} \end{array}$$

$$\sqrt{\frac{g_{jk}}{\Sigma_{j=1}^{p}(g_{jk})}} = \begin{array}{l} \text{j's}\downarrow \text{ k's} \rightarrow \\ \textit{they} \\ \textit{spend} \\ \textit{too} \\ \textit{much} \end{array} \begin{array}{c} \begin{matrix} \textit{people} & \textit{issues} & \textit{beliefs} & \textit{candidates} & \textit{help} & \textit{waste} \end{matrix} \\ \begin{bmatrix} 0.17 & 0.16 & 0.15 & 0.16 & 0.18 & 0.16 \\ 0.03 & 0.03 & 0.02 & 0.02 & 0.03 & 0.08 \\ 0.06 & 0.08 & 0.05 & 0.07 & 0.06 & 0.11 \\ 0.06 & 0.06 & 0.06 & 0.07 & 0.06 & 0.11 \end{bmatrix} \end{array}$$

$$\begin{array}{l} \\ \textbf{\textit{they spend too much}} \\ \textit{they represent the middle class} \\ \textit{their stance on abortion} \end{array} \begin{array}{c} \begin{matrix} \textit{people} & \textit{issues} & \textit{beliefs} & \textit{candidates} & \textit{help} & \textit{waste} \end{matrix} \\ \begin{bmatrix} 0.16 & 0.16 & 0.14 & 0.16 & 0.17 & \mathbf{0.23} \\ \mathbf{0.23} & 0.19 & 0.18 & 0.18 & \mathbf{0.24} & 0.17 \\ 0.11 & \mathbf{0.19} & \mathbf{0.18} & 0.14 & 0.10 & 0.12 \end{bmatrix} \end{array}$$

Table B.1: We illustrate calculations for the transformed document-term matrix. Each row of the transformed matrix is standardized (see text) prior to singular value decomposition. The leading dimension of this method will capture the number of words and use of more common words across documents, and the next will be the first substantive dimension.

the top candidate dimensions to correlate with different measures of attitudes (after the leading dimension, which captures only the number of words and how common they are), and for assessing stability over time.

Prior to applying SVD, we standardize the data: $\sqrt{\frac{m_{ik}}{\Sigma_{k=1}^{q} m_{ik}}}$. Since singular vectors correspond to the eigenvectors of $X^\top X$ and $XX^\top$, this standardization ensures that each respondent is weighted equally, and the square root here allows the first singular vector to more fully capture document length and word frequency, leaving subsequent dimensions to reflect more substantive variation. For data with weights, we can multiply the observations by the square root of the weight (and also use a weighted document-term matrix to create the conditional word distributions). Somewhat less important, though in keeping with our arguments on the importance of frequent words over rare words, we can further constrain the calculations to only q relatively common words (i.e., only calculating that documents are about common words rather than all words), with q substantially smaller than the total number of words p – for example, just the words that are used more than average. For our analyses, we restrict this to the number of words whose squared frequency is greater than the average squared frequency. We show in the Supplementary Tables and Figures section of the appendix that we see the same results for word frequencies simply greater than the

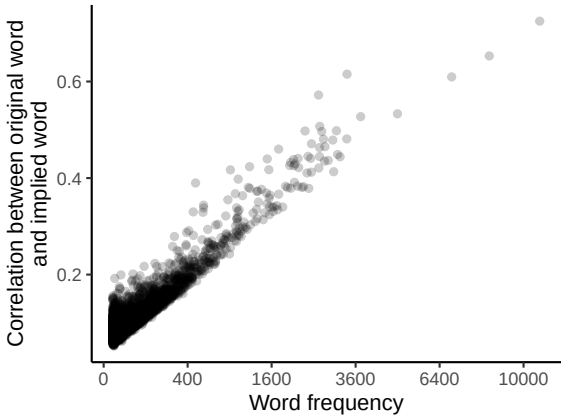


Figure B.2: This figure shows the correlation between words in the original document-term matrix and the 'implied' words in the transformed matrix. More rare words are not strongly correlated with their original use because they have been rescored to reflect the associations of the common words appearing in the same document.

average frequency. However, with that setting, the dimensions are sometimes highly correlated with each other, and have the potential to exaggerate the reliability of the findings (e.g., if all dimensions are moderately correlated with the first substantive dimension).

To score uncommon words on the same basis as common words – especially for documents that do not contain the common words used in the scaling – we multiply the transposed and standardized conditional word co-occurrence matrix by the right singular vectors, as if we had decomposed the (transposed and standardized) conditional word co-occurrence matrix rather than the implied word matrix. This has little effect on the scores for common words, while placing more rare words into the same scoring space.

Finally, we apply the scoring vectors to the original document-term matrix to produce document scores. Putting the scoring process together, with $\boldsymbol{D}$ representing the document-term matrix, $\boldsymbol{G}$ the standardized word co-occurrence matrix/sampling distribution matrix, and $\boldsymbol{V}$ the right singular vectors of singular value decomposition of $\boldsymbol{M}$, the transformed document-term/'implied word' matrix describe above, document scores are produced by the matrix multiplication $\boldsymbol{D}(\boldsymbol{G}^\top \boldsymbol{V})$ and then standardized so that each observation has a Euclidean norm of one. Word scores – for both common and rare words – are $\boldsymbol{G}^\top \boldsymbol{V}$.

When listing keywords, we multiply word scores by the square root of words' frequencies and then report the top words with the largest values on each side of the scale. This multiplication ensures that the keywords reflect the influence of common words on the scaling process, as illustrated in Figure B.2 – we treat common and rare words equally when assigning document scores.

C Implied word method: R code walk-through

Step 1. Calculate implied words

Our first step in the implied word method is to calculate the similarity between documents and common words – meaning, a word that is common in the provided set of open-ended responses.

For this, we calculate the similarity of **a)** the distribution of words *in a given document* and **b)** the distribution of words across all documents *that contain a given common word*.

The more the distribution of words in a document resembles the distribution of words across all documents (*in the prompt-specific corpus*) that contain a given focal word, then the more we say that document is 'about' / 'implies' that word – whether or not the focal word is itself used in the document. Note that in the calculation below similar use of frequent words will more strongly influence the 'implied word' similarity score than similar use of infrequent words (as we illustrated in the previous section).

1.1. Calculate co-occurrences of words from a document-term matrix. Rows of this matrix are documents (one row for each document) and columns are words (one column for each word). For the elements of this matrix, 1 indicates the presence of a word in an open-ended response and 0 its absence. In the R code, we use sparse matrices (and the packages `Matrix` and `RSpectra`) to speed up calculations – sparse matrices use empty values in place of 0's.

```
cooccurrence_matrix <- Matrix::crossprod(document_term_matrix)
```

The diagonal of this matrix is the number of times that a word was used in the corpus and off-diagonals are the numbers of co-occurrences of (pairs of) words.

optionally, weight the document-term matrix prior to calculating the co-occurrence matrix:

```
cooccurrence_matrix <- Matrix::crossprod(
  weight_matrix(document_term_matrix, w=weights)
)
```

1.2. Row-standardize the co-occurrence matrix to get the distribution of words (in each row of this matrix). These distributions represent the square root of probabilities used when calculating the Bhattacharyya coefficients.

`row_standardize_matrix()`, in effect, divides each row by its sum (for row-wise probabilities) and then applies an element-wise square root (for later input into a Bhattacharyya coefficient calculation). The function is written slightly differently than this explanation to speed up computation.

```
standardized_cooccurrence_matrix <- row_standardize_matrix(cooccurrence_matrix)
```

$$\sqrt{\frac{g_{kj}}{\sum_{j=1}^{p}(g_{kj})}}$$

This step does not affect the final output when all elements in the document-term matrix are 1 or 0, as they are here.

```
standardized_document_term_matrix <- row_standardize_matrix(document_term_matrix)
```

$$\sqrt{\frac{d_{ij}}{\sum_{j=1}^{p}(d_{ij})}}$$

1.3. Subset standardized co-occurrence matrix to common words:

First, find words above the frequency cutoff

```
word_counts <- colSums(document_term_matrix)
common_words <- word_counts^2 >= mean(word_counts^2)
# or word_counts >= mean(word_counts)
```

And then truncate the standardized co-occurrence matrix, leaving only (square roots of) the distributions of common words. Note that we truncate here to avoid excessive calculations – we could also have truncated our implied word matrix, truncating the implied word matrix to the top q implied/common words.

```
truncated_cooccurrence_matrix <- standardized_cooccurrence_matrix[common_words,]
```

1.4. Calculate Bhattacharyya coefficients – matrix multiply standardized document-term matrix and transpose of truncated co-occurrence matrix:

```
implied_word_matrix <- standardized_document_term_matrix %*% t(truncated_cooccurrence_matrix)
```

$$m_{ik} = BC(d_i, g_k)_{ik} = \sum_{j=1}^{p} \sqrt{\frac{d_{ij}}{\sum_{j=1}^{p}(d_{ij})}} \sqrt{\frac{g_{jk}}{\sum_{j=1}^{p}(g_{jk})}}$$

Step 2. Find dominant variation in implied words

The next step is to find dimensions in the standardized implied word matrix that explained the largest variance in that matrix. We are not only interested in common words – we are specifically interested in common words that strongly vary/co-vary across respondents.

For this, we use singular value decomposition.

2.1. Standardize the implied word matrix, so that documents influence the decomposition more equally (with unequal influences coming in through the optional weighting below):

```
standardized_implied_word_matrix <- row_standardize_matrix(implied_word_matrix)
```

2.2. Run singular value decomposition:

```
svds <- RSpectra::svds(standardized_implied_word_matrix, k=10)
```

optionally, weight matrix prior to decomposition:

```
svds <- RSpectra::svds(
  weight_matrix(
    standardized_implied_word_matrix,
    w = weights
  ),
  k = 10
)
```

Step 3. Score documents

After finding the dimensions that explain the largest variance in implied word usage, we score the original documents on those dimensions.

3.1. Extract word scores:

```
word_score_matrix <- svds$v
```

optionally (but recommended), if many respondents do not use common words in their responses, use right singular vectors to score all words based on their standardized co-occurrences with common words:

```
word_score_matrix <- standardized_cooccurrence_matrix[,common_words] %*%
  svds$v
```

There is no transpose in this step as in the main text only because we aligned our description there with column-oriented notation – note the transpose and switch in notation from steps 1.2 to 1.4 above – and we wrote this R code to consistently run row-wise standardizations.

3.2. Apply word scores to documents:

```
scored_documents <- document_term_matrix %*% word_score_matrix
```

3.3. Standardize scored documents to have a Euclidean norm of 1 (similar to document scores summing to 1 in a topic model):

```
standardized_scored_documents <- euc_row_standardize_matrix(scored_documents)
```

We use the `standardized_score_documents` matrix for our analyses. The first column of this matrix, which we name `X0`, is closely related to word frequency. The second column, `X1`, is a substantive dimensions – e.g., the "issues/positions/ideology" versus "groups/performance/candidates" dimension in the partisan likes and dislikes analysis.

Step 4. Get keywords

Last, we can extract keywords using a combination of a word's polarity on a dimension and its frequency. We number dimensions starting at 0, since dimension 0 captures word frequency. Later dimensions capture variation in word use beyond mere frequency.

This code assumes that matrix columns are named (with their corresponding words).

```
vocab <- colnames(document_term_matrix)
# distance from word score mean times square root of word frequency
dimension_number <- 1
frequency_weighted_and_centered_word_scores <- scale(
  word_score_matrix[,dimension_number+1], center = TRUE, scale = FALSE
) * # polarity
  sqrt(word_counts) * # frequency
  common_words # common word subset (from Step 1)

vocab[order(frequency_weighted_and_centered_word_scores, decreasing = T)][1:15]
vocab[order(frequency_weighted_and_centered_word_scores, decreasing = F)][1:15]
```

Standardization and weighting functions

We have reduced these functions to their bare-bones functionality, and explain their function in comments because they are written for fast sparse matrix calculations with the `Matrix` R package.

```
row_standardize_matrix <- function(m) {
  #### this function standardizes the rows of a matrix
  #### these calculations are equivalent to standardizing each row to sum to 1
  #### and then taking the square root of each value/probability
  if (class(m)=="dsCMatrix") {
    m <- as(m, "dgCMatrix")
  }
  ## transpose so that later operations are on columns
  ## (which are rows of the original matrix)
  m <- Matrix::t(m)
  ##
  row_norm <- sqrt(Matrix::colSums(m))
  m@x <- sqrt(m@x) /
    rep.int(row_norm, diff(m@p))
  ## transpose back to original format
  m <- Matrix::t(m)
  return(m)
}
```

```
euc_row_standardize_matrix <- function(m) {
  #### this function standardizes the rows of a matrix
  #### so that each row has a Euclidean norm of 1
  if (class(m)=="dgeMatrix") {
    m <- as(m, "dgCMatrix")
  }
  ## transpose so that later operations are on columns
  ## (which are rows of the original matrix)
  m <- Matrix::t(m)
  ##
  row_norm <- sqrt(Matrix::colSums(m^2))
  m@x <- m@x /
    rep.int(row_norm, diff(m@p))
  ## transpose back to original format
  m <- Matrix::t(m)
  return(m)
}
```

```
weight_matrix <- function(m, w) {
  #### this function multiplies each row
  #### by the square root of the observation weight
  ##
  m <- Matrix::t(m)
  ##
  m@x <- m@x *
    rep.int(sqrt(w), diff(m@p))
  ##
  m <- Matrix::t(m)
  return(m)
}
```

Putting all scoring steps together

```
# input: document_term_matrix -- rows are document, columns are words
# 1 or 0 for occurrence of word in document
# use sparse representation for computational efficiency
library(Matrix)
library(RSpectra)

# output matrix: word co-occurrences
cooccurrence_matrix <- Matrix::crossprod(
  weight_matrix(document_term_matrix, w=weights)
)

# output matrix: word distributions, square roots of probabilities
standardized_cooccurrence_matrix <- row_standardize_matrix(cooccurrence_matrix)
standardized_document_term_matrix <- row_standardize_matrix(document_term_matrix)

# output matrix: square roots of probabilities, truncated to common words
word_counts <- colSums(document_term_matrix)
common_words <- word_counts^2 >= mean(word_counts^2)
truncated_cooccurrence_matrix <- standardized_cooccurrence_matrix[common_words,]

# output matrix: implied words
implied_word_matrix <- standardized_document_term_matrix %*%
  t(truncated_cooccurrence_matrix)
standardized_implied_word_matrix <- row_standardize_matrix(implied_word_matrix)

# SVD
svds <- RSpectra::svds(
  weight_matrix(
    standardized_implied_word_matrix,
    w = weights
  ),
  k = 10
)

# output matrix: word scores
word_score_matrix <- standardized_cooccurrence_matrix[,common_words] %*%
  svds$v

# output matrix: scored documents
scored_documents <- document_term_matrix %*% word_score_matrix
standardized_scored_documents <- euc_row_standardize_matrix(scored_documents)
```

Step 5. Adding embeddings (optional)

We can use implied word document scores and embeddings to create an embedded version of the implied word method. The logic of this process is much like using embeddings for the term "positive" minus embeddings for the term "negative" as a zero-shot sentiment classifier (see, for example, a similar approach here: https://platform.openai.com/docs/guides/embeddings/use-cases). Here, we use the positive and negative ends of the implied word document scores, after centering, to find a contrast embedding.

5.1: multiply document implied word scores by embeddings and average to get implied word embedding. The example below calculates this embedding for only dimension 1 of the implied word method (numbering starts at 0, since 0 is a frequency dimension).

```
# inputs:
# documents scored with implied word method (documents on rows, dimensions in columns)
# document embeddings (documents on rows, embedding dimensions in columns)
# label embeddings (labels on rows, embedding dimensions in columns)

library(text2vec)

# output: implied word embedding for dimension 1 (one row, n embedding dimensions columns)
implied_word_embedding_1 <- colMeans(
  (scored_documents[,2] - mean(scored_documents[,2])) * document_embeddings
)
```

optionally, subtract the weighted mean and calculate weighted column-wise means:

```
implied_word_embedding_1 <- apply(
  (scored_documents[,2] - weighted.mean(scored_documents[,2], w=weights)) *
    document_embeddings,
  2,
  weighted.mean,
  w = weights
)
```

5.2: calculate the cosine similarity of each document with the implied word embedding:

```
# output: document-level implied word embeddings for dimension 1
# (documents in rows, one column for embedded implied word score)
scored_documents_1 <- text2vec::sim2(
  document_embeddings, implied_word_embedding_1,
  method = "cosine"
)
```

5.3: calculate top labels for poles of implied word dimension using cosine similarity: In the main paper, top labels are the labels with the 100 highest and 100 lowest cosine similarities.

```
# input: label embeddings (labels in rows, embedding dimensions in columns)

# output: label scores (one row, n labels columns)
scored_labels_1 <- text2vec::sim2(
  implied_word_embedding_1, label_embeddings,
  method = "cosine"
)
```

Collected guidance for using the implied word method

This user guide collects guidance provided in the main text of the article into one convenient location.

Users of the implied word method can install the `impliedWords` package from `https://github.com/wilryh/impliedWords`, and use that R package to run the method. The github site will also host this user guide (/ an updated version of it).

Before using the method, open-ended survey data must be processed into a document-term matrix format. See the R package for an example on how to do this using the `stm` package.

Hyperparameters

The implied word method has few hyperparameters for users to choose from, and we recommend that users mostly rely on the settings used for the main analysis in this paper.

Those settings are:

- Setting 'common words' equal to the words whose squared frequency is greater than the average squared frequency
  - this can alternatively be set to frequency greater than average frequency, if a user thinks that important words may have been left below the cutoff
  - however, we have rarely observed meaningful differences when changing this setting – and any differences may merit investigation (e.g., the introduction of outliers when lowering the cutoff)
- Projecting rare words – meaning that all words will be scored by the method, rather than just the common words
  - this can alternatively be set to score only rare words, if a user would like to assess sensitivity to scoring only common words

Pitfalls

After running the implied word method, users should assess whether there are large outliers influencing the output.

Outliers

Outliers can have a large influence on the scored dimensions. We have encountered a few main scenarios where this can happen:

- the corpus includes responses in different languages
  - for example, if a corpus contains both English and Spanish – but primarily English – then the Spanish words will tend to be very large outliers and have a substantial influence on the scored dimensions

- respondents have copied identical text from the web into their response
  - for example, many respondents copying parts of their answers from the same Wikipedia page will tend to lead to large clusters of outlying word scores

- insufficient data cleaning has left clusters of responses that contain the same text indicating "no response" – for example, "Respondent did not answer"

To check for outliers, we recommend plotting the word scores using the `plot_keywords` function in the `impliedWords` package. When there are outliers, this plot will show words that are very far from the rest of the words (typically in the 1st and 2nd dimensions) and/or the majority of word scores in only half or a corner of the plot (with the outliers being very small or below the function's word frequency cutoff).

Corpus 'context size'
The context covered in some corpora may be too large for our method to work well – for example, when what is contextually common for one subset of the data is not contextually common for the other. For this, we can split the data on some variable that may drive overly large context size (and a contrast that we know we do not want the method to identify – e.g., pandemic versus non-pandemic years) and assess the correlation in word frequencies across that contrast. The `impliedWords` package will soon implement this check.

Interpretation and in-depth validation

We recommend an in-depth validation of the implied word method's output when using it in research. This validation can focus primarily on an accurate and transparent interpretation of the output.

Interpreting dimensions and keywords in context
To interpret dimensions, we recommend that users plot word scores and list keywords, as well as read a sample of documents by their associated document scores. A sample of documents by document scores should also be provided in articles that use the method (see, for example, the tables in SI Section K of this article).

Users can further incorporate the generative AI and embedding descriptive approach we use in the main text of this paper (with full details in the SI). This labeling can be helpful prior to more time-intensive and costly hand labeling, or in combination with it. Without pre-existing hand labels, it may be challenging to efficiently describe the contents of a dimension to the reader of an article who may not have access to many of the texts to read themselves, since our method relies on context-specific and potentially symbolic meanings of words. Lists of keywords may not always be informative on their own, and information contained in lists of documents may be difficult to efficiently convey to readers.

In validating interpretations, we recommend users assess associations with existing hand labels or create a set of hand labels that can more or less reproduce the output of the implied word method. Users can refer to research on best practices for coding potentially complex constructs from, for example, Benoit et al. (2016) and Tanweer et al. (2021). Here, we caution that coders may need to be given appropriate context to code texts appropriately, and that researchers will likely need to critically assess crowd worker performance in context – potentially iterating on provided context and instructions.

Last, users should assess dimensions' associations with metadata covariates (e.g., year, gender, education, party). Dimensions can be associated with a covariate and still be valid (some constructs *should* be associated with covariates like party and education). However, dimensions are not guaranteed to conform to researcher expectations. it is possible for the primary variation in an open-ended response to be communication style, just as a closed-ended responses can be dominated by social desirability or acquiescence bias. Associations with covariates can provide useful information for accurately and transparently interpreting dimensions.

Hand labeling

The implied word method is useful primarily for uncovering dimensions in text that tend to be highly stable over time and so more likely to represent stable attitudes. We anticipate that the vast majority of useful constructs recovered by the implied word dimension will be codeable by hand, and perceptible to a human reader (*after* the dimension has been identified).

Because of this, we recommend that researchers create a codebook to reproduce and validate the automated output of the implied word method whenever possible. Researchers can code the dimension directly or indirectly (through, for example, coding complex constructs using combinations of simpler and easier to code features in text). As also mentioned above, coders may need to be given appropriate context to code texts appropriately, and researchers will likely need to critically assess crowd worker performance in context – potentially iterating on provided context and instructions.

The process of creating and implementing the codebook should clarify the interpretation of dimensions, and allow for replication of findings across different measurement approaches (with potentially different sources of error).

Use of multiple open-ended responses

We can use multiple open-ended questions to assess possible style effects. If our first dimensions represent communication style only, then we might observe strong correlations over time between different questions. In our article, this test was not definitive – ideally, we would have a method that would be able to capture shared political content across multiple, potentially related political questions. Completely unrelated questions or a political versus non-political question would be preferable for this evaluation.

D Twitter analysis

D.1 Word frequency and month-to-month correlations in user word re-use

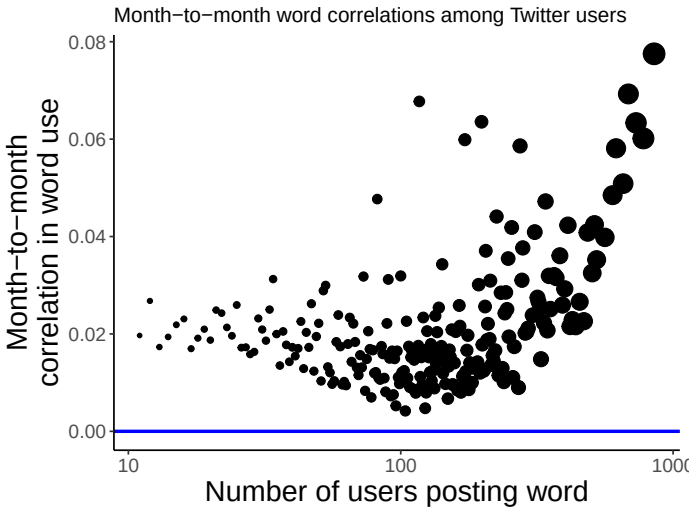


Figure D.1: *Correlation in word use over time in social media posts.* The blue line in this figure is a horizontal line at correlation equal to 0. Each point represents a group of words, excluding stop words from the English language 'snowball' stop word list. Words are grouped by word frequency, and we plot the average correlation within each bin. This data is drawn from a large sample of Twitter users who have been linked to voter records and whose tweets have been continuously collected since 2017 (Hughes et al. 2021). The correlations analyzed here cover the period January 2019 through June 2022 (given a tweet collection issue starting in July 2022 that is now being resolved) and, for computational reasons, a random 10% sample of the overall Twitter panel (approximately 100 thousand users).

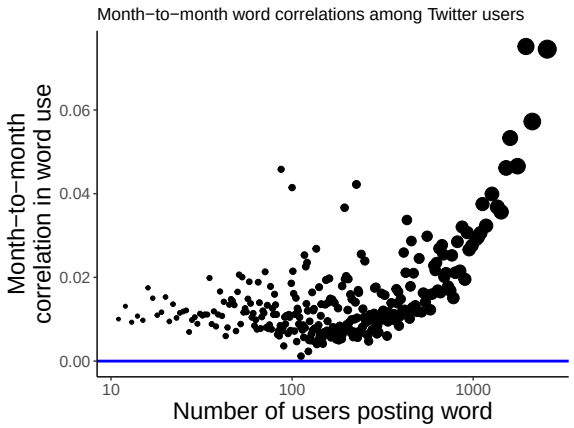


Figure D.2: *Correlation in word use over time in social media posts.* This figure repeats Figure D.1, limiting the sample to tweets containing 'political' keywords in the following categories (following keywords and categories in Green (2023)): class, climate, conservative, democrat, far-left, far-right, gender, guns, health, immigration, lgbt, liberal, progressive, race, reproductive health, republican, tax and spending policy, trade. Keywords are excluded from the correlation analyses.

D1 (-)	(+) D1	D2 (-)	(+) D2
health	racist	gop	gay
care	white	democrats	racism
climate	republican	republican	trans
via	republicans	republicans	racist
new	gop	trump	black
change	party	election	people
medicare	democrats	senate	white
crisis	gay	biden	women
join	shit	house	men
u.s	like	party	like
tax	democrat	democrat	community
medicaid	trump	vote	love
access	ass	via	can
workers	man	president	feminist
insurance	racists	impeachment	i'm

Table D.1: Implied word method keywords – 'political' content only. Keywords categories used in filtering: class, climate, conservative, democrat, far-left, far-right, gender, guns, health, immigration, lgbt, liberal, progressive, race, reproductive health, republican, tax and spending policy, trade. In addition to removing non-political content, this filtering also removes highly repetitive spam content (e.g. enter-to-win sweepstakes posts).

E Supplementary Tables and Figures

E.1 ACA attitudes: keywords, panel correlations, and hand label multiple R's

E.1.1 ACA attitudes: keywords

Implied word method

D1 (-)	(+) D1	D2 (-)	(+) D2
people	government	people	care
insurance	much	going	health
health	involved	lot	government
everyone	going	pay	access
coverage	cost	know	believe
afford	money	help	needs
access	everything	insurance	involved
conditions	want	money	everyone
helps	control	helps	affordable
affordable	run	just	everybody

Table E.1: Implied word method: top 2 substantive dimension keywords (ACA attitudes). Note that the first dimension of this method reflects word frequency, and we label it dimension 0.

Zero-shot PC's

D1 (-)	(+) D1	D2 (-)	(+) D2
helping	screwed	money	doesnt
positive	terrible	financial	without
helps	sucks	pay	dont
beneficial	failure	economic	illness
helpful	oppose	prices	opinion
helped	bad	economically	otherwise
good	poorly	paying	illnesses
help	opposed	budget	freedom
right	disagree	price	patient
providing	unfair	dollars	less

Table E.2: Zero-shot method: top 2 substantive dimension keywords (ACA attitudes)

E.1.2 ACA attitudes: panel correlations and hand label multiple R's

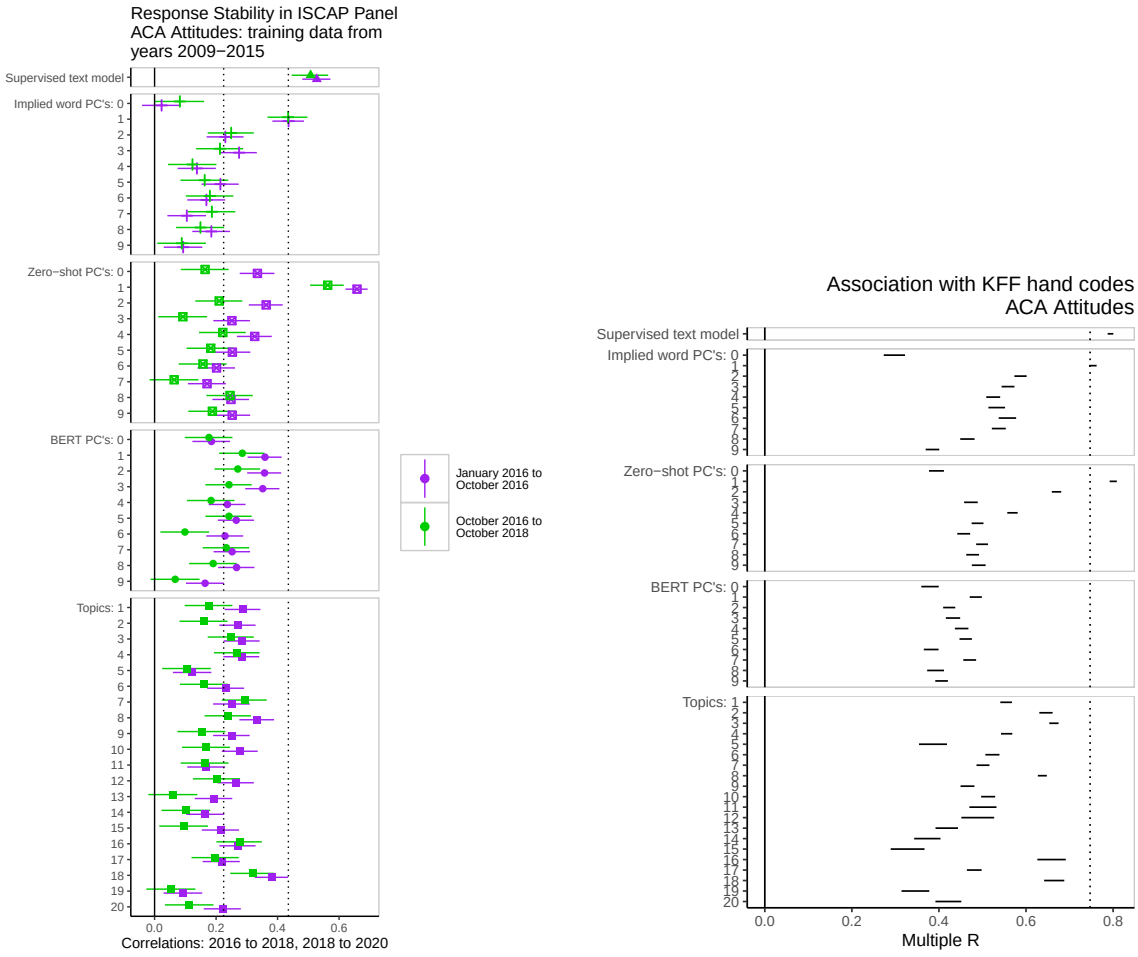


Figure E.1: The hand label multiple R analysis is limited to labels occurring at least 10 times and across 2 waves (this is lower than in the ANES analysis because there were fewer labels occurring in many waves).

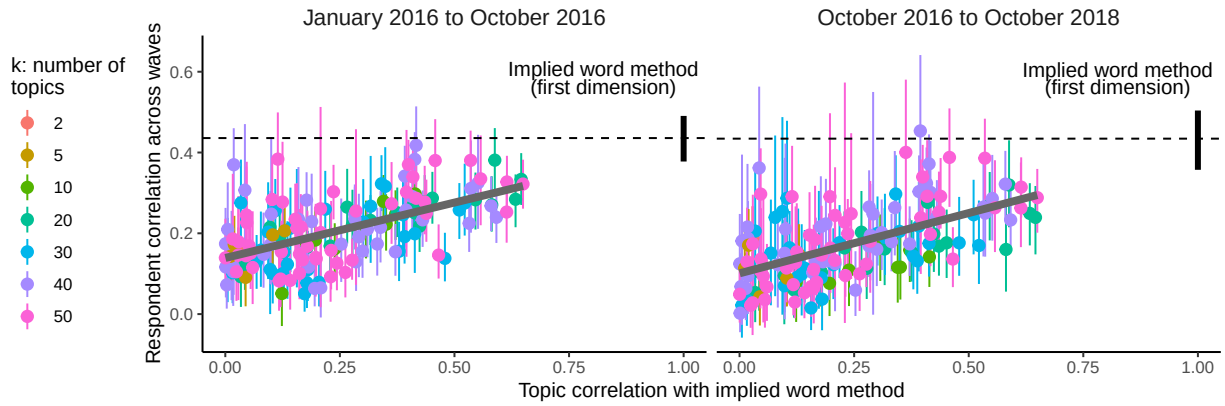


Figure E.2: Test-retest correlation and correlation with the first dimension of the implied word method for topic models across multiple settings of k (the number of topics): Affordable Care Act responses.

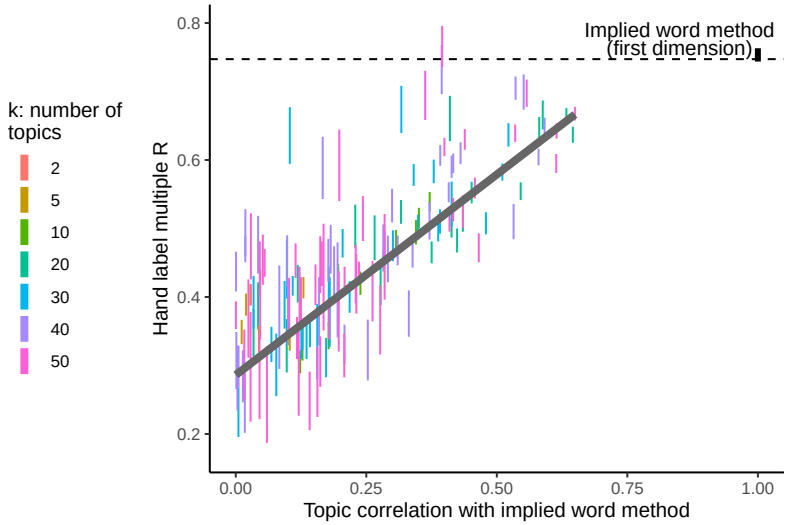


Figure E.3: Hand label multiple R's and correlation with the first dimension of the implied word method for topic models across multiple settings of k (the number of topics): Affordable Care Act responses.

E.1.3 ACA attitudes: alternate 'common word' cutoff

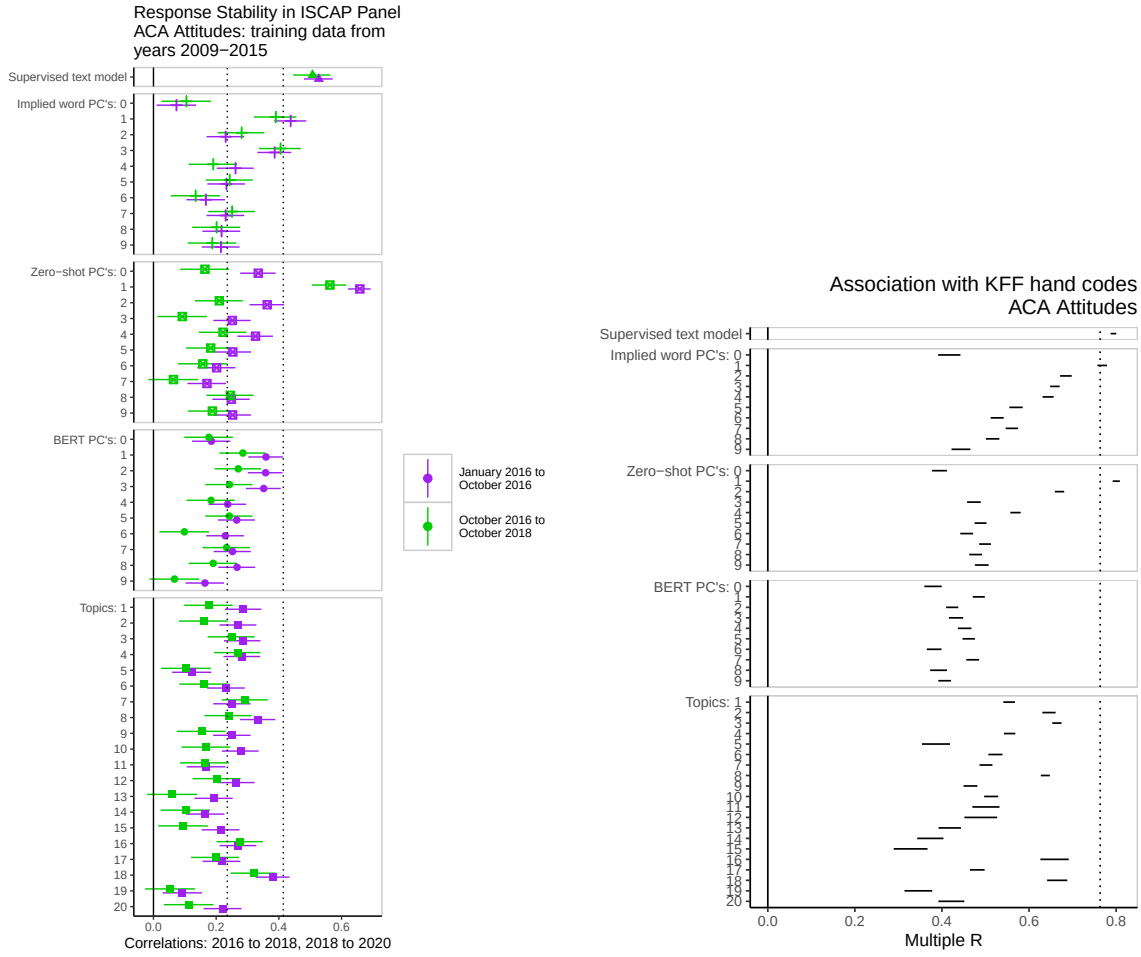


Figure E.4: This figure repeats the findings in Figure E.1 for 'common words' that have a frequency greater than the average frequency of words.

E.2 Party likes/dislikes: keywords and issue preferences on first dimension of implied word method

E.2.1 Party likes/dislikes: keywords

Implied word method

D1 (-)	(+) D1	D2 (-)	(+) D2
abortion	people	class	trump
rights	rich	middle	president
stance	poor	rich	party
gun	class	poor	candidate
pro	working	people	together
views	get	lower	parties
issues	help	tax	right
conservative	always	help	good
marriage	man	social	vote
gay	middle	working	republican

Table E.3: Implied word method: top 2 dimension keywords (party likes/dislikes). Note that the first dimension of this method reflects word frequency, and we label it dimension 0.

Zero-shot PC's

D1 (-)	(+) D1	D2 (-)	(+) D2
helping	negative	personal	especially
supportive	dislike	service	alot
positive	bad	lack	something
good	wrong	economically	among
right	opposed	working	strongly
helps	disagree	economy	appears
inclusive	dishonest	families	particularly
encourage	blame	wage	things
help	anti	fiscally	regarding
supporting	extreme	feeling	minded

Table E.4: Zero-shot method: top 2 substantive dimension keywords (party likes/dislikes).

E.2.2 Party likes/dislikes: issue preferences on first dimension of implied word method

Figure E.5 shows that the first dimension of the implied word method, people versus issues, is strongly associated with policy stances but not aligning with partisan stances on those issues. In Figure E.6, we show that some of this pattern is due to non-linearity. Most people who discuss issues and stances are more liberal on abortion, but those specifically mentioning abortion (and at the most extreme end of the dimension) are more conservative on the issue.
Issues here were chosen because they were included on a large number of ANES waves.

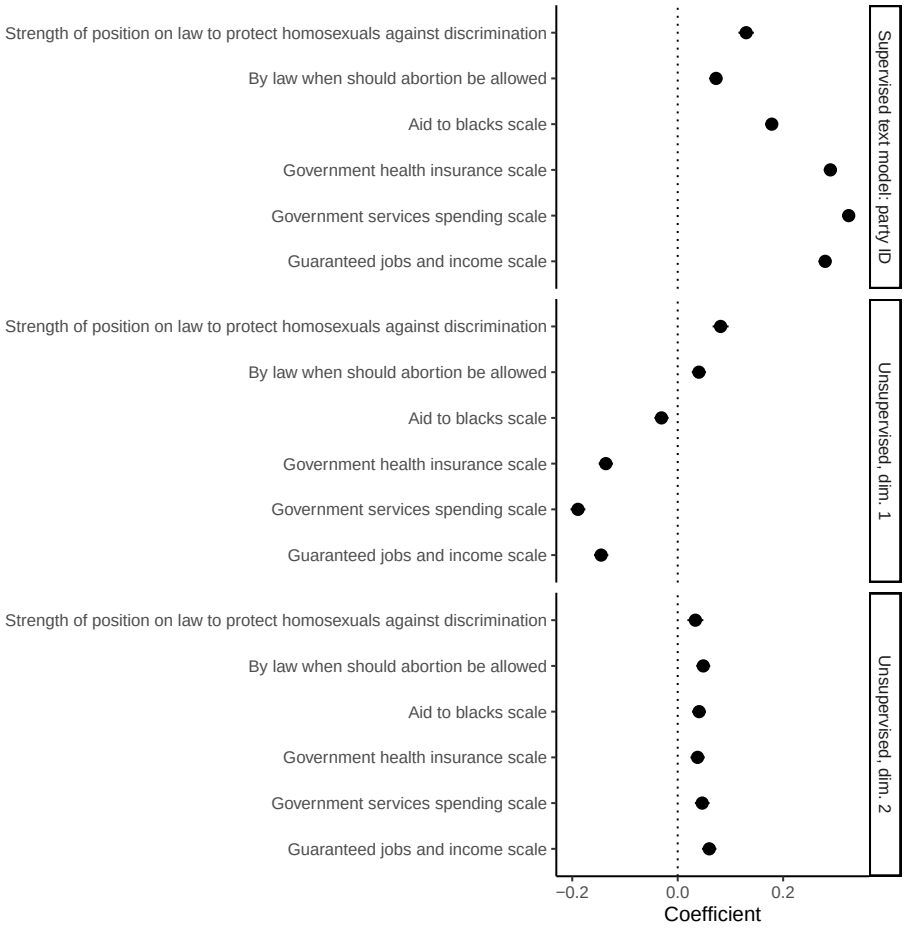


Figure E.5: Association between unsupervised implied word scores and policy stances compared to supervised model of party ID. All policy stances are coded so that higher values on the scale are more conservative.

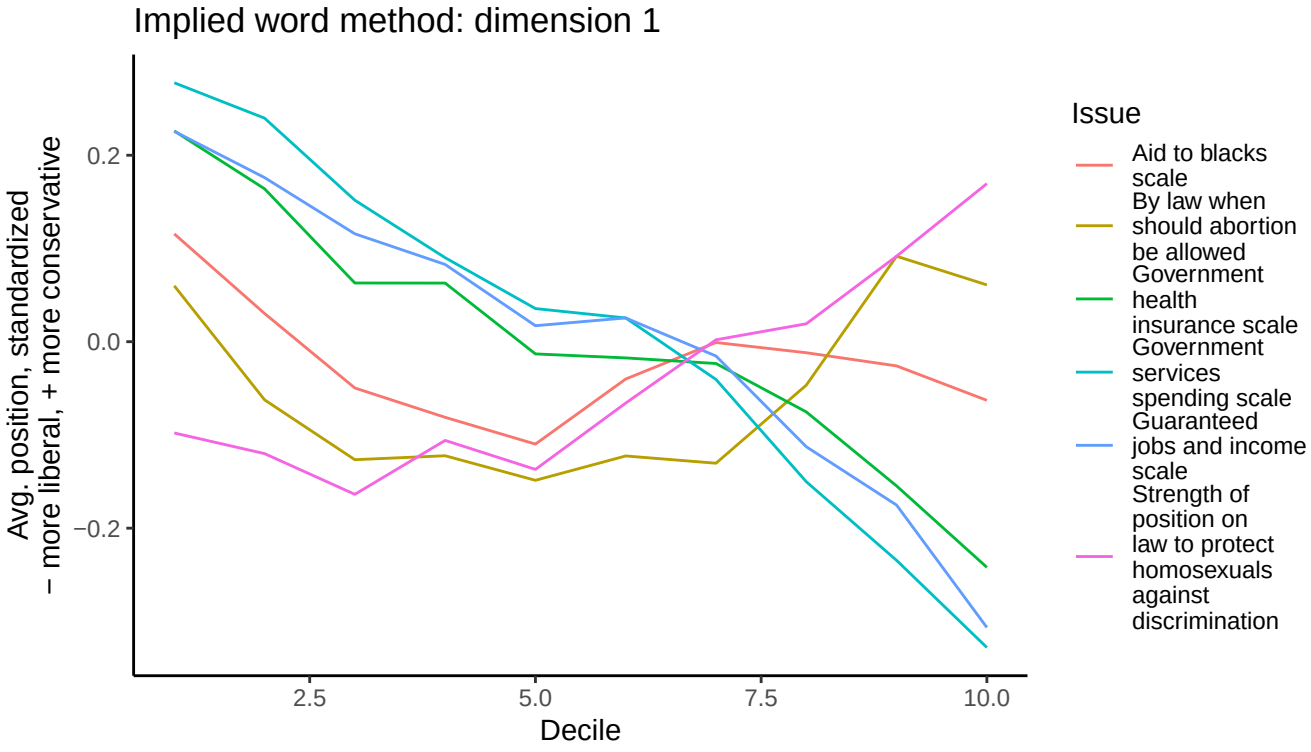


Figure E.6: This figure shows non-linearity in some issue preferences in the first dimension of the implied word method. For example, respondents tend to be more conservative on 'By law, when should abortion be allowed' when they either specifically mention abortion or talk generally about groups when answering what they like or dislike about the parties.

E.2.3 Party likes/dislikes: alternate 'common word' cutoff

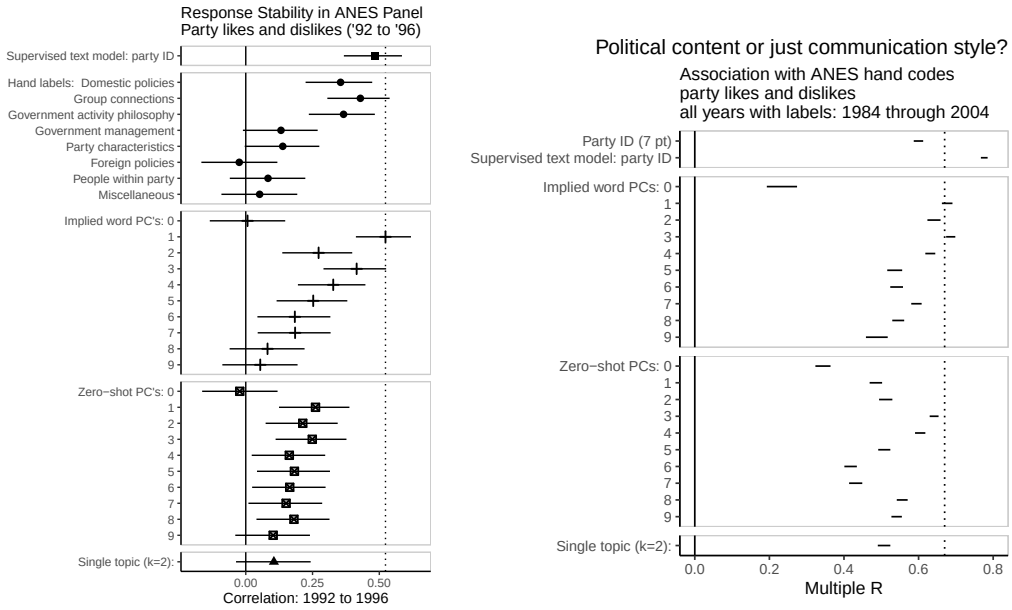


Figure E.7: This figure repeats the findings in Figures 3 and 4 for 'common words' that have a frequency greater than the average frequency of words. This specification was not used in the main results because many of the dimensions were highly correlated with the top substantive dimensions, potentially exaggerating reliability of lower dimensions.

E.3 Party likes/dislikes: illustration of coherence vs stability in topic models

To illustrate our point that topic models, as used in current practice, do not reliably produce categories with high test-retest reliability (and so more likely to reflect attitudes), we show below the correlations over time for hand selected topics that we perceived to have high coherence. These topics seemed to have a relatively cohesive set of keywords.

For this purpose, we ran a correlated topic model with the "stm" package (Roberts et al. 2016) as in our main analyses, but allowing the software package to select the number of topics automatically (following (Mimno and Lee 2014)). We came away with a model containing 69 topics. From there, we looked at each topic's keywords as selected by the high frequency and exclusivity value (Bischof and Airoldi 2012), using the package default of 0.5. We then selected a small number of topics that seemed to us to have the highest coherence, meaning that we would tend to group these words together (when thinking about politics, though not necessarily in the context of this question).

Last, we studied the 2016-2020 correlation in these topics. We focused on 2016-2020 because we have far more data than for 1992-1996, we need more data to study relatively sparse topics (from a model with 69 topics), and also because the topic models, in not accepting weights like our implied word method, may have better captured variation in responses during that period in which there were many more open-ended responses from the online sample.

The findings show that these topics widely varied in their correlations over time. Figure E.8 on the next page displays these correlations and Figure E.9 on the page after shows that these correlations are not driven by large shifts in *overall* topic prevalences from 2016 to 2020. To us (though of course we can begin to rationalize the results after seeing them), it was not obvious which of these clusters would be most strongly correlated over time when we only chose them based on keywords – other than our awareness of which ones seemed to most closely resemble the output of the implied word method.

Broadly, our point here is that 1) topic models produce many topical categories that are not strongly correlated over time, 2) we need panel data to understand the stability of responses, 3) the coherence of topic keywords can tell us little about the expected stability of a response, or an underlying, stable attitude, and 4) correlation with our implied word method (as we demonstrate in Figure 3 tends to be a better indicator of response stability than coherence.

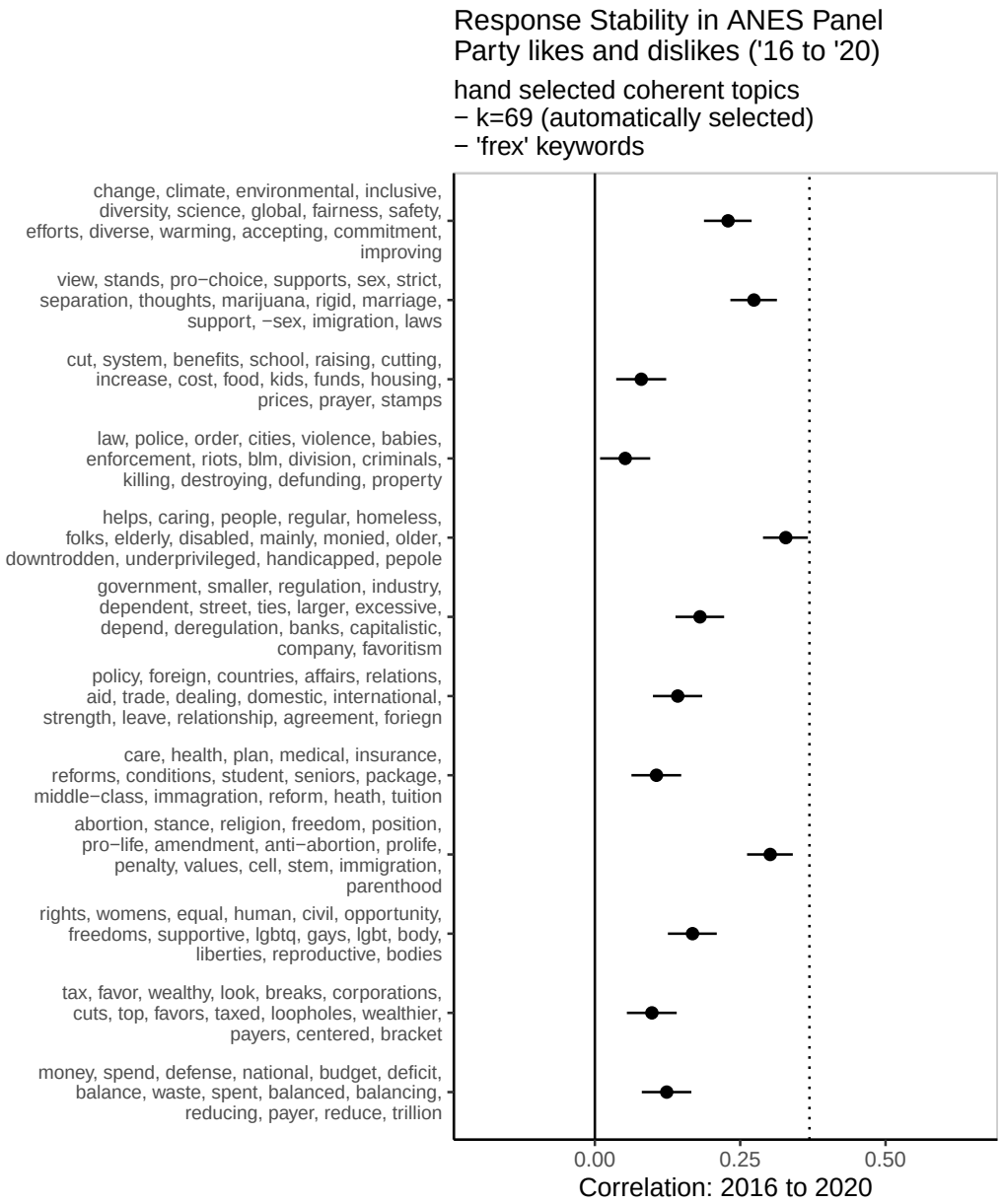


Figure E.8: 2016-2020 test-retest reliability of coherent topics from the party likes/dislikes data, ordered by topic number.

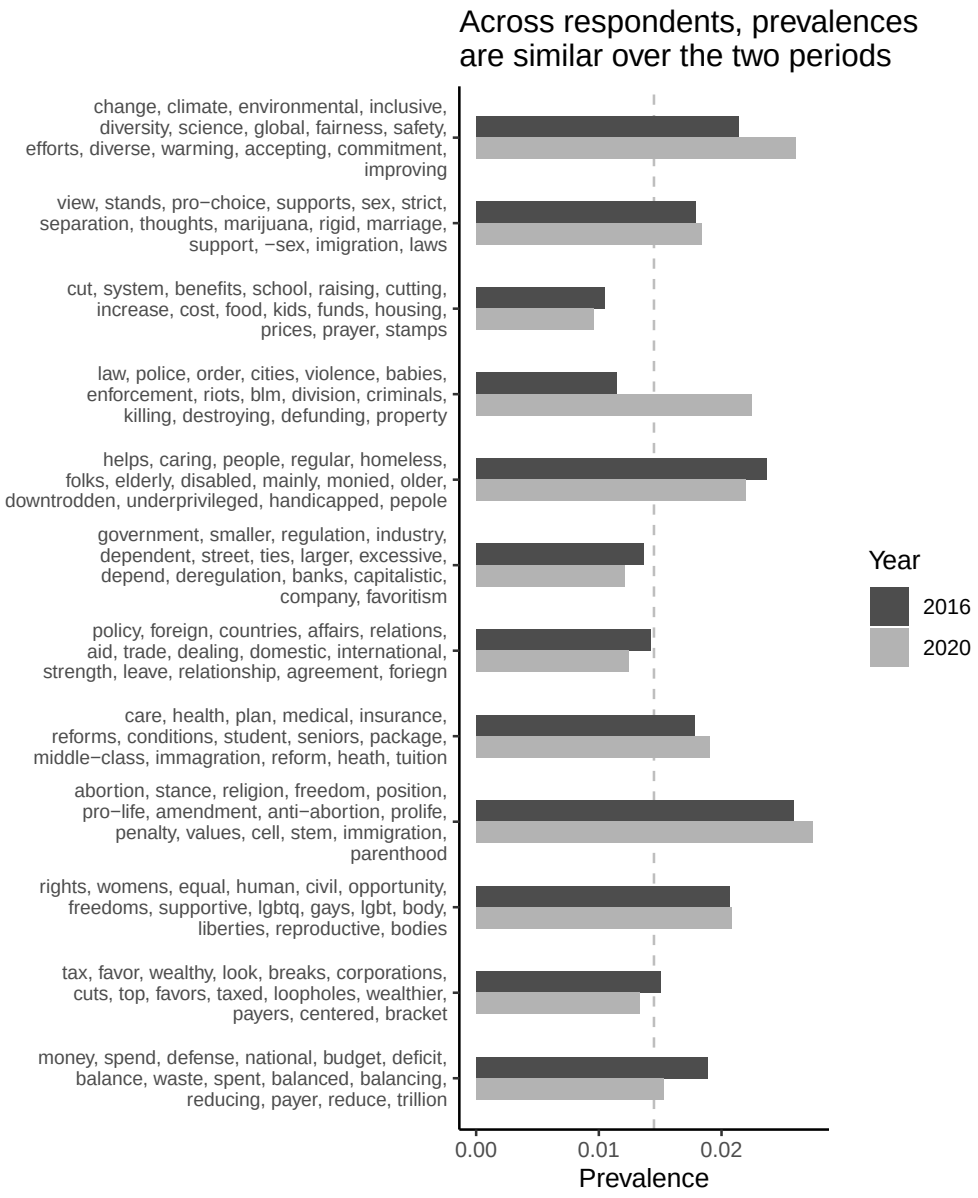


Figure E.9: 2016-2020 prevalences of coherent topics from the party likes/dislikes data. The vertical gray line indicates the value $\frac{1}{69}$.

E.4 Party likes/dislikes: response distinctiveness

We contrast the common word approach with an approach that emphasizes response distinctiveness. By response distinctiveness, we mean that responses could be categorized primarily by how different they seem compared to other responses in a corpus. For this, we use BERT sentence embeddings (Devlin et al. 2018) and, with linear regression, the difference between the average embedding location for documents that contain a given word versus the average for documents that do not. Response distinctiveness is the Euclidean distance between those averages. This follows the approach in embedding regression for studying differences in language use across groups (Rodriguez et al. 2023).

The left panel of E.10 shows that the most frequently-used words are among the likeliest to be re-used. These may reflect 'issue publics' (Krosnick 1990) or 'easy issues' (Carmines and Stimson 1980; Abramowitz 1995). The right panel of Figure E.10 shows the association between response distinctiveness for sentences containing a word, and that word's 2016-2020 correlation. Here, by contrast, we do not observe any relationship between response distinctiveness and word re-use. While common words alone are far from perfect indicators of stable attitudes, they are more informative than response distinctiveness.

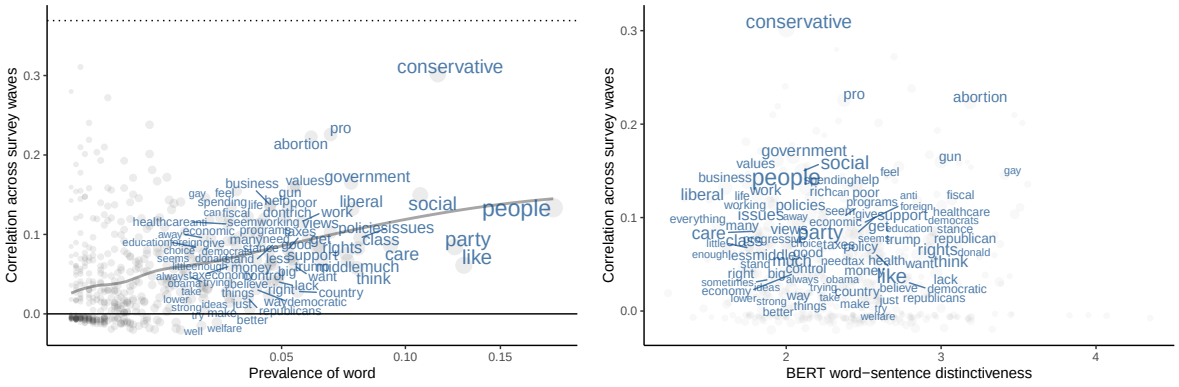


Figure E.10: Response distinctiveness versus word frequency.

E.5 Most important problem: keywords

E.5.1 Most important problem:: keywords

Implied word method

D1 (-)	(+) D1	D2 (-)	(+) D2
people	economy	war	health
children	deficit	nuclear	education
kids	war	arms	lack
get	budget	going	healthcare
school	terrorism	russia	care
schools	foreign	countries	racism
just	unemployment	get	immigration
work	east	now	crime
can	relations	reagan	affordable
pay	nuclear	know	insurance

Table E.5: Implied word method: top 2 dimension keywords (most important problem). Note that the first dimension of this method reflects word frequency, and we label it dimension 0.

Zero-shot PC's

D1 (-)	(+) D1	D2 (-)	(+) D2
support	destruction	economics	moral
helping	terrible	economic	abuse
improved	destroying	economy	attitude
improve	bad	supporting	morality
help	threats	improving	corrupt
improving	destroy	helping	opinion
provide	hurting	improve	conflict
assistance	crisis	important	unrest
benefits	trouble	worked	divisiveness
supporting	threat	together	mind

Table E.6: Zero-shot method: top 2 substantive dimension keywords (most important problem)

E.5.2 Most important problem: alternate 'common word' cutoff

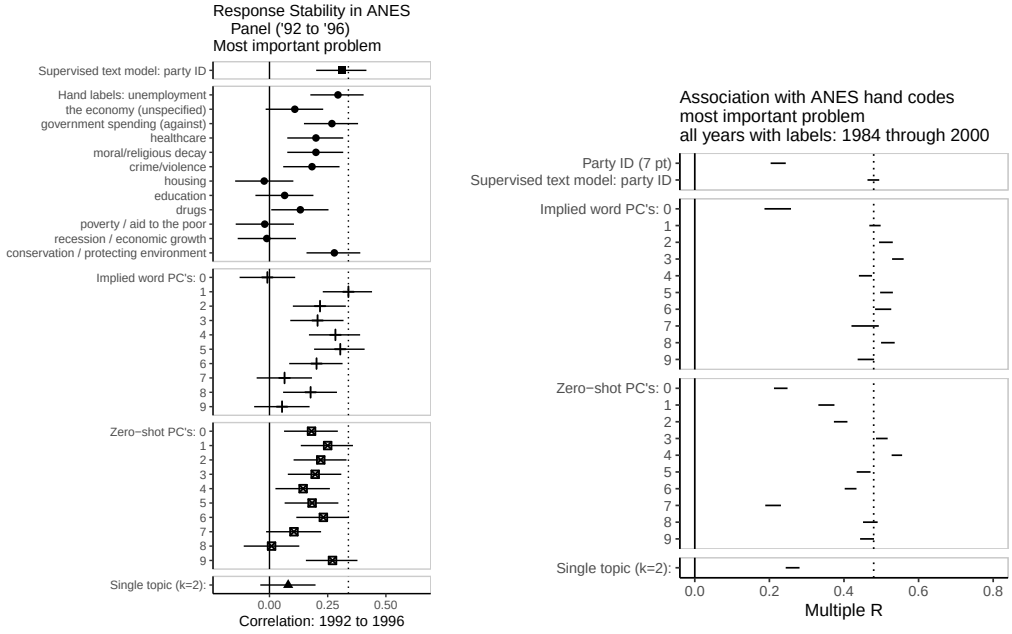


Figure E.11: This figure repeats the findings in Figures 3 and 4 for 'common words' that have a frequency greater than the average frequency of words.

F "Common" words?

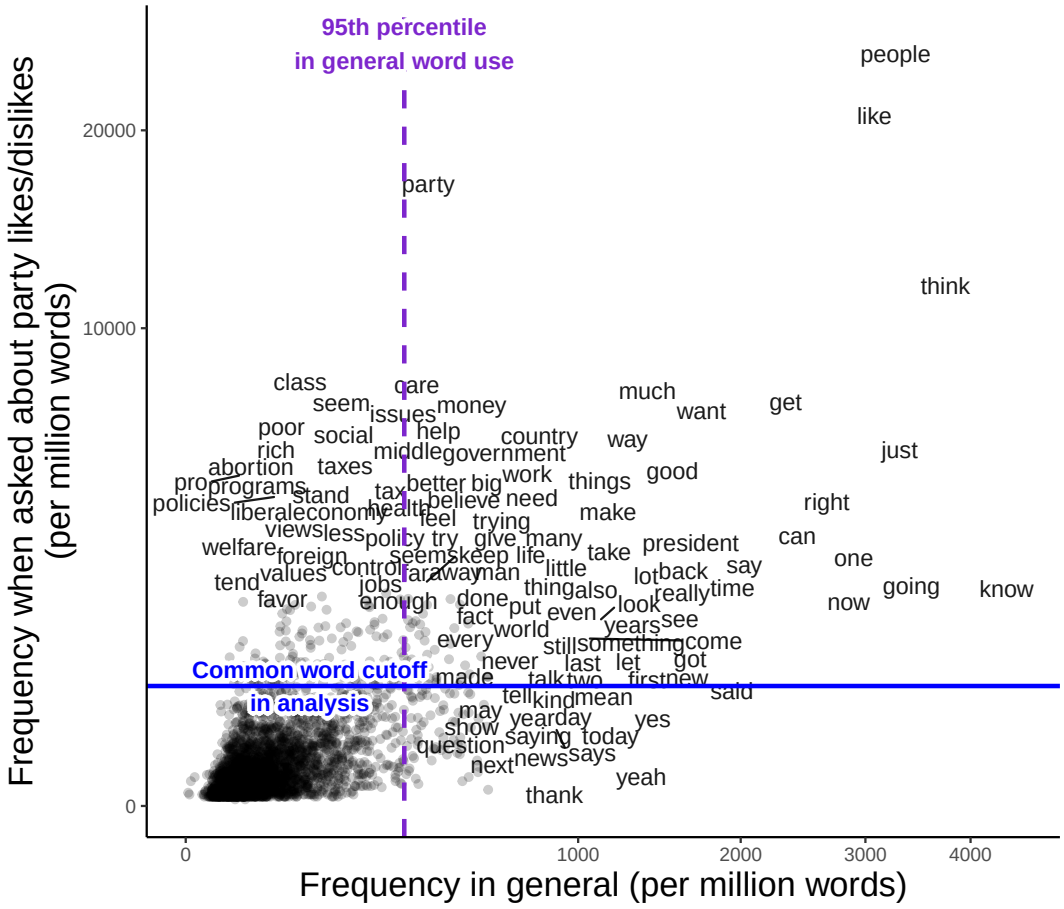


Figure F.1: Frequencies of words in response to the party likes and dislikes prompts versus frequencies of words in general use. Frequencies of general word usage are from the "spoken" genre of the Corpus of Contemporary American English (COCA) (Davies 2008). Words that are moderately common in general can be very common in response to a focused prompt. Corpus frequencies differ somewhat from Figure 3 because that analysis is limited to 2016-2020 ANES panelists, and because the scale here is by frequency per million words to align with the COCA frequency data.

G An example pair of responses about the Affordable Care Act

We argue that, to the extent to which sophisticated statements are informative of attitudes, it is typically through their use of common words, *or* those statements' resemblance to statements that *do* contain common words, that allow the listener (or in our case, the researcher) to place that statement in context. The use of highly idiosyncratic language – however sophisticated – is not by itself informative of attitudes and does not reliably provide additional, relevant information beyond words that are more commonly-used in the given context.

For example, consider two responses in our data concerning the Affordable Care Act from the same respondent in January and October 2016, respectively:

January 2016: *It allows me to continue to cover my daughter after college and I like the no pre existing condition part of it. Lastly, it gives many people a chance to get healthcare coverage they need.*

October 2016: *I like that it allows parents to cover there children longer, no pre existing conditions, clearer EOBs for patients to understand, EHRs, data exchanges, and insurance exchanges to promote insurance competition.* [sic]

Both of these relatively detailed statements (most respondents provide a single short reason for support or opposition) contain multiple words that are common in the particular context of discussing the Affordable Care Act – "conditions" and "coverage", for example, appear together on the pole of the first dimension from our method in Figure 2 – and some rare words (e.g., "EOBs," "EHRs," "exchanges"). Our point is that these contextually common words are more informative of the respondent's general attitudes about the Affordable Care Act – including the stable elements of their responses over time – than the more idiosyncratic rare words, even though they may signal sophistication on the part of the respondent.

Rare words do still matter in our analyses, however. Although they have less influence on dimensions of the implied word method, less common words such as "data" or "exchange" are still scored with respect to each dimension – based on their co-occurrence with more common words.

H Adding latest generation embeddings

H.1 Generating labels with GPT 3.5

We prompted GPT 3.5 (through Microsoft Azure) to return topical labels for every open-ended response across each of the questions analyzed in the main text. The goal of this process was only to produce a large number of labels that *could* be applied to the open-ended responses. We analyzed the labels using embeddings (see next section, Section H.2).

Like (Mellon et al. 2022), we prompted GPT 3.5 with 50 open-ended responses at a time. Responses were grouped randomly. To generate labels, we used the following prompts:

Affordable Care Act responses

> Here are open-ended responses to a question about the Affordable Care Act that asked "Could you tell me in your own words what is the main reason you have (a favorable/unfavorable) opinion of the health reform law?":
>
> [50 survey responses, each on a new line]
>
> Please assign some topical categories to each open ended text response.
>
> GUIDELINES: Return all of the original survey responses, their ID numbers, and their most relevant categories. There are likely to be multiple relevant categories, many of which will not be words in the survey response itself. The number of relevant categories is likely to vary across responses. As an example response format, please return in this format:
> id:1|"survey response text"|"category1","category2"
> id:2|"survey response text"|"category3","category2","category5","category6".

Party likes/dislikes responses

> Here are open-ended survey responses to a question about American political parties that asked "Is there anything in particular that you (like/dislike) about the (Democratic/Republican) party? What is that?":
>
> [50 survey responses, each on a new line]
>
> Please assign some topical categories to each open ended text response.
>
> GUIDELINES: Return all of the original survey responses, their ID numbers, and their most relevant categories. There are likely to be multiple relevant categories, many of which will not be words in the survey response itself. The number of relevant categories is likely to vary across responses. As an example response format, please return in this format:
> id:1|"survey response text"|"category1","category2"
> id:2|"survey response text"|"category3","category2","category5","category6".

Most important problem responses

> Here are open-ended survey responses to a question that asked "What do you think is the most important problem facing this country today":
>
> [50 survey responses, each on a new line]
>
> Please assign some topical categories to each open ended text response.
>
> GUIDELINES: Return all of the original survey responses, their ID numbers, and their most relevant categories. There are likely to be multiple relevant categories, many of which will not be words in the survey response itself. The number of relevant categories is likely to vary across responses. As an example response format, please return in this format:
> id:1|"survey response text"|"category1","category2"
> id:2|"survey response text"|"category3","category2","category5","category6".

GPT 3.5 would often not return labels for many of the texts that we submitted. We did not spend much time trying to fix this behavior because we only wanted a long list of labels, and did not need response level categories from this generative AI step.

H.2 Embedding labels and documents with the OpenAI v3 large embedding model

We used the OpenAI `text-embedding-3-large` model to embed each open-ended response as well as every category returned by GPT 3.5 (as described above in Section H.1). We also added text around the open-ended responses to provide minimal context. We added this same contextualization for the BERT comparisons included alongside the OpenAI embedding results. We did not contextualize embeddings for the GPT generated labels, since they are used for the purpose of assisting readers with interpreting implied word output (with limited context awareness). Before further analyses (i.e., embedding the implied word method as well as running principal component analysis on the embeddings), we averaged each respondent's party likes/dislikes embeddings. All other data sets contained only one response per respondent. This averaging had the effect of removing information that indicated only which party likes/dislikes question a respondent was answering (and so without this averaging returning only the information we already had in closed-ended form).

For contextualization, we used the following prompts:

Affordable Care Act responses

> Here is an open-ended response to a public opinion survey question about the Affordable Care Act that asked "Could you tell me in your own words what is the main reason you have (a favorable/unfavorable) opinion of the health reform law?":

[1 survey response]

The respondent gave this answer sometime between 2009 and 2018.

Question: Broadly speaking, what is the main reason this respondent has a favorable or unfavorable opinion of the Affordable Care Act?

Party likes/dislikes responses

Here is an open-ended response to a public opinion survey question that asked "Is there anything in particular that you (like/dislike) about the (Democratic/Republican) party? What is that?":

[1 survey response]

The respondent gave this answer in a United States presidential election year sometime between 1980 and 2020.

Question: Broadly speaking, why does this respondent like or dislike the Democratic or Republican party?

Most important problem

Here is an open-ended response to a public opinion survey question that asked "What do you think is the most important problem facing this country today?":

[1 survey response]

The respondent gave this answer in a United States presidential election year sometime between 1980 and 2020.

Question: Broadly speaking, what does this respondent think is the most important problem or problems facing the United States?

H.3 Embedding the implied word method output

To create an embedding for each dimension of our implied word method, we centered the implied word document scores at each dimension's weighted mean (each ANES survey wave was weighted equally), and multiplied the implied word document scores by each document's embedding (see previous section, Section H.3). We then averaged the embeddings (i.e., we averaged each of the 3,072 dimensions for the OpenAI embeddings and 768 for BERT) to return an embedding for each implied word dimension. For analyses with a hold-out set in the implied word method training (e.g., the ACA analyses and the ANES analyses trained only on 2016 data), the same data was also held out for this dimension embedding step.

H.3.1 Scoring documents with embeddings

An implied word document score for the embedded version of the method is simply the cosine similarity between a given document's embedding and the implied word embedding (for a given dimension) described above. See the R code walk-through in Section C for an implementation this scoring process.

Similarly, the document score for a topical label (those generated by GPT 3.5 – for the analysis displayed in the bottom panel of Figure 6) is the cosine similarity between a given document's embedding and the label's embedding.

H.4 Top embedding labels for each open-ended question

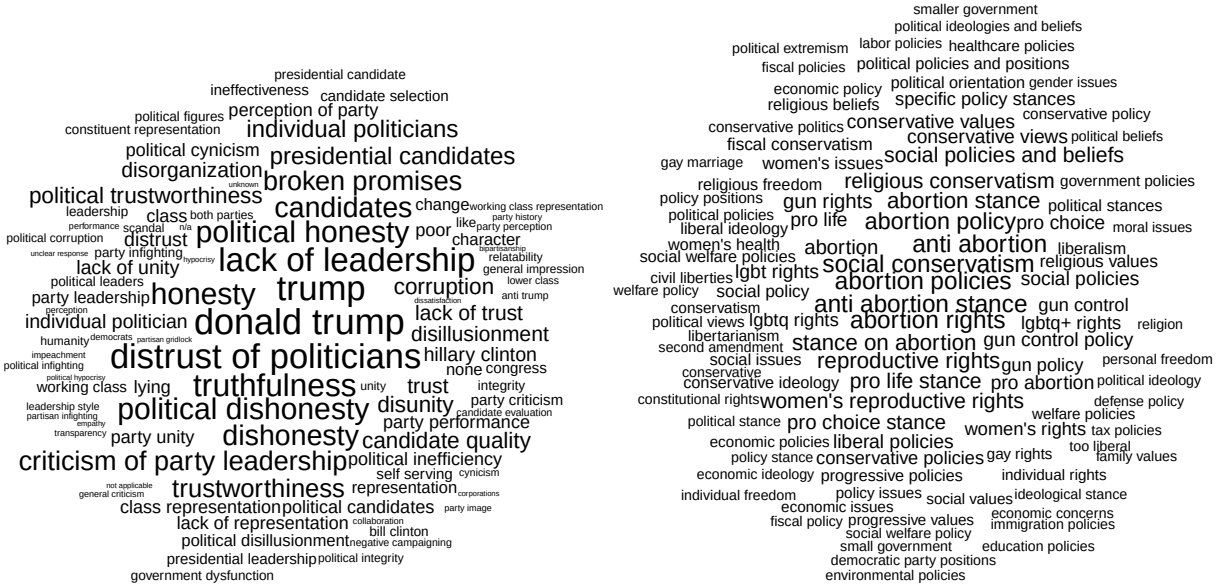
Affordable Care Act

Party likes/dislikes

Most important problem

GPT 3.5 generated category labels with the 100 highest and 100 lowest cosine similarities for the first embedded implied word dimension of each open-ended question.

Party likes/dislikes



Most important problem

GPT 3.5 generated category labels with the 100 highest and 100 lowest cosine similarities for the first embedded implied word dimension of each open-ended question – trained on 2016 data only.

H.5 Embedding panel correlations

Below, we show the full results for the top 10 dimensions of the implied word method and the top 10 dimensions for PCA on the BERT and OpenAI embeddings.

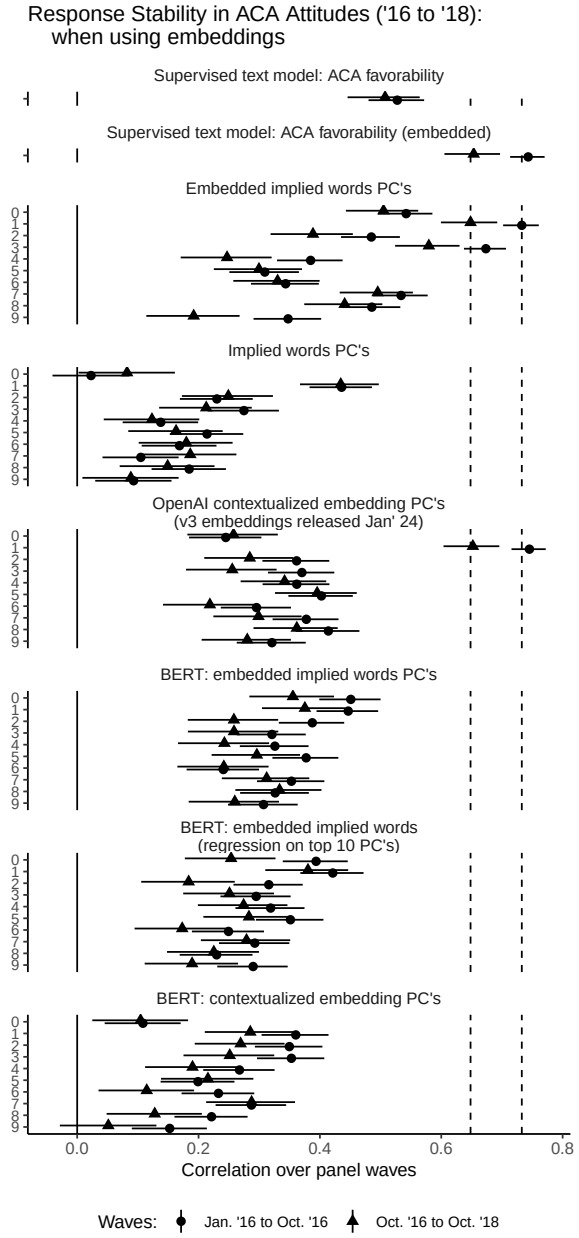


Figure H.3: Test-retest correlations for the embedded version of our method, along with PCA dimensions from BERT and OpenAI v3 embeddings – Affordable Care Act responses.

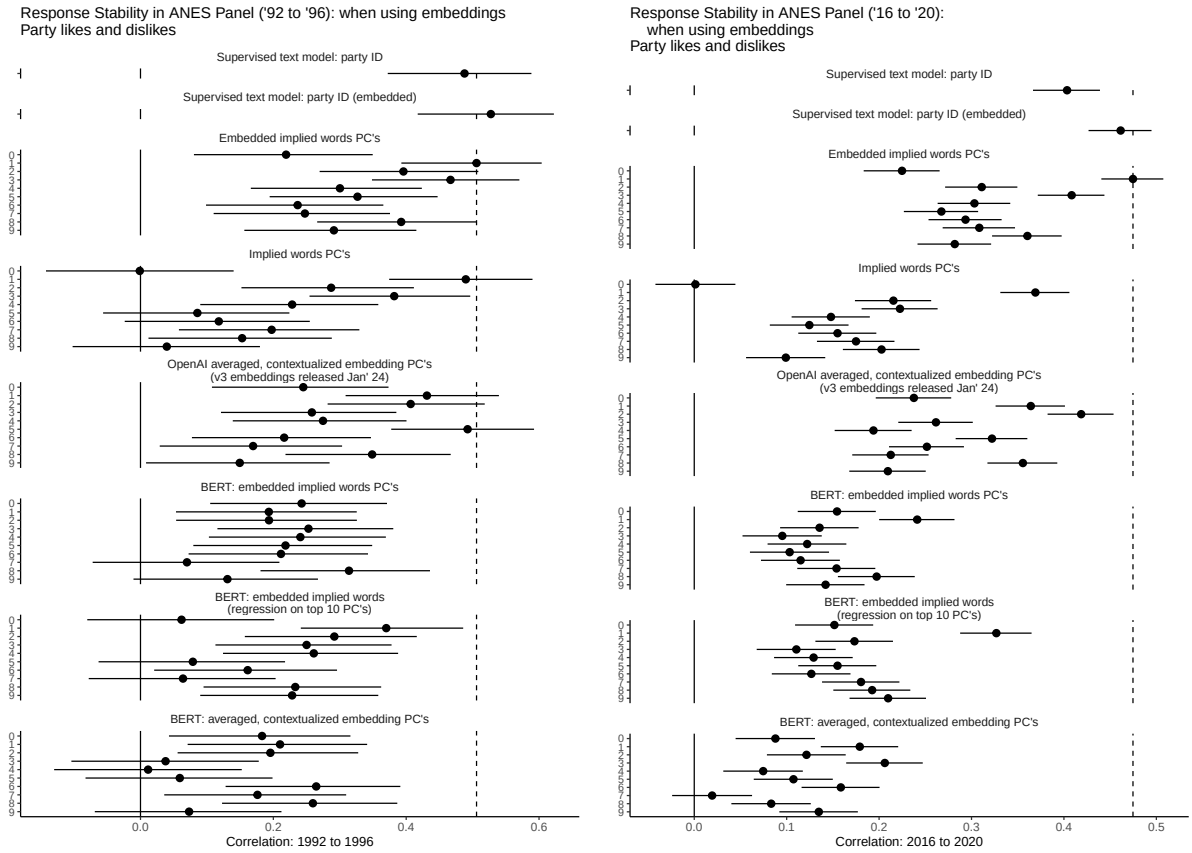


Figure H.4: Test-retest correlations for the embedded version of our method, along with PCA dimensions from BERT and OpenAI v3 embeddings – party likes/dislikes responses.

We speculate a few reasons that the new embeddings might out-perform BERT: 1) they are just bigger (e.g., 3,072 dimensions versus 768) and so can better capture variation in meaning (though this can plausibly also work against them), 2) they have more relevant training data (and the ability to better identify relevance), potentially including the ANES data itself (unfortunately, training data details are not public for these models, even to our knowleedge 'open-source' models, and 3) they are trained with and for a longer and more expansive context/context window and so, relevant to our task here, capture a broader sense of topics than more narrow windows.

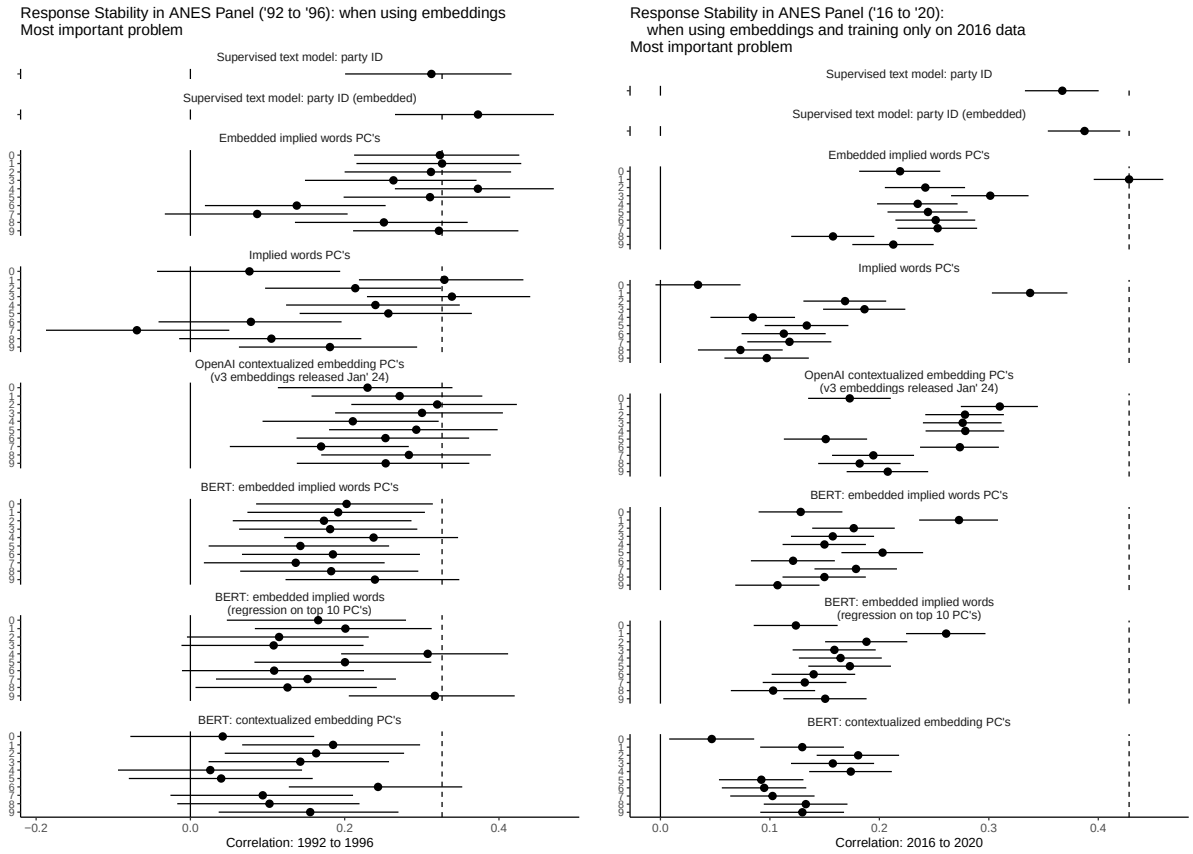


Figure H.5: Test-retest correlations for the embedded version of our method, along with PCA dimensions from BERT and OpenAI v3 embeddings – most important problem responses.

H.6 Embedding correspondence with hand labels

We show a hand label multiple R analysis for the embedding analyses below, following the same procedure we used to generate Figure 4.

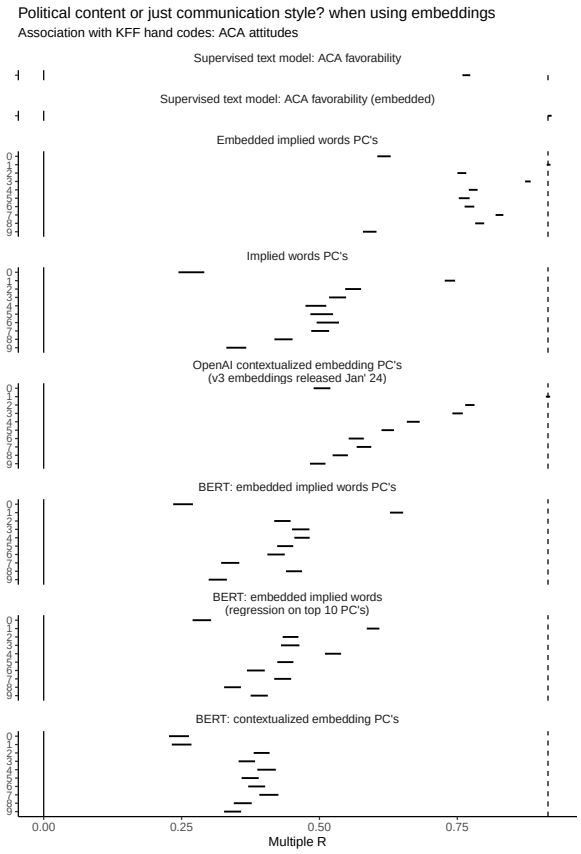


Figure H.6: Embedded method hand label multiple R's – Affordable Care Act responses. The first dimensions of the embedded implied word and OpenAI embedding PCA have very narrow confidence intervals and are on top of the dotted line.

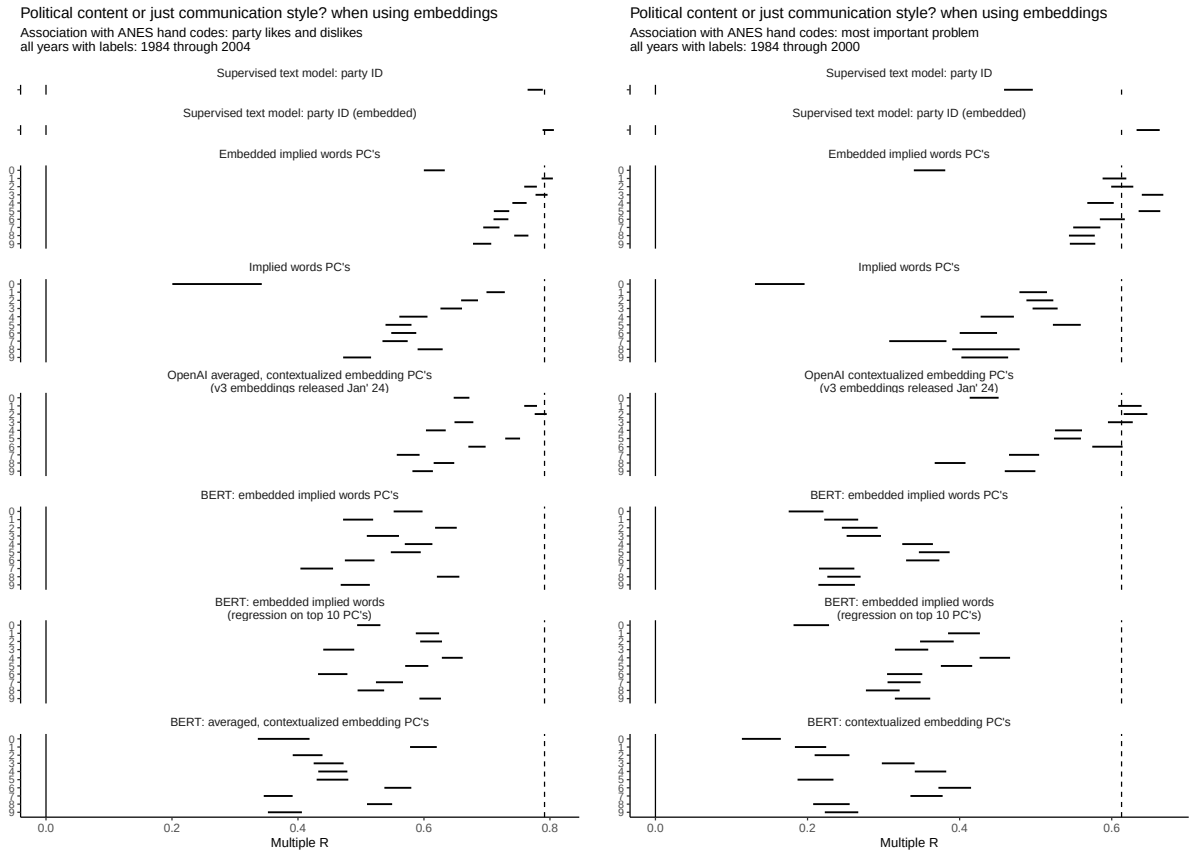


Figure H.7: Embedded method hand label multiple R's – party likes/dislikes and most important problem responses

I Assessing corpus 'context size'

The context covered in some corpora may be too large for our method to work well – for example, when what is contextually common for one subset of the data is *not* contextually common for the other, or when the associations with those contextually common words differ substantially (and so, potentially, convey different symbolic meanings).

To assess this, we can split the data on some variable that may drive overly large context size and a contrast that *we know we do not want the method to identify* – e.g., pandemic versus non-pandemic years. We can then assess the correlation in word frequencies across that contrast.

Below, we show that over a shorter 4 year interval (rather than close to 40 years), even with a pandemic, 2016 (only) and 2020 do not meaningfully differ in terms of common word use (i.e., correlation in square root word frequencies). In this figure, black circles around the points indicate survey waves that are 4 years or fewer apart.

In the main text, we retrained our implied word method using just 2016 as training data for both ANES questions. This gave us an extra test for our added, latest generation embedding analyses, and also allowed us to better compare test-retest reliability and cross test-retest reliability.

Note that this test does not mean that the implied word method will *necessarily* be strongly influenced by the examined contrast. For example, we do not observe meaningful differences for the most important problem question when excluding 2008 (which asked a different question: "What do you think is the most important *political* problem facing the United States today?" – emphasis added). This appears to be because 2008 differs from the rest of the corpus primarily on the (first) dimension that the implied word method identifies even without that year included in training (i.e., this wording reduces the number of political issues mentioned that are also societal issues). 2020, on the other hand, includes much more novel information.

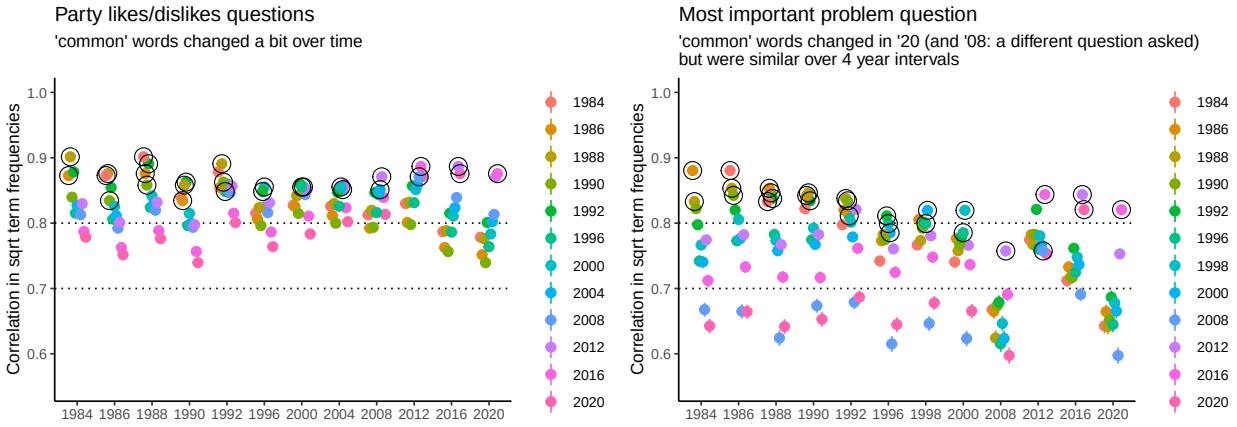


Figure I.1: Correlations in square root word frequencies, and so contextually common words and their associates, diverge in 2020 for the most important problem question, but are similar to those in 2016 – suggesting that a 40 year context size is too large for this question but a 4 year context size is not. Black circles around the points indicate survey waves that are 4 years or fewer apart.

J Response length and response stability

We were uncertain whether document length might be incorporated into our method in some way.

Longer responses could reflect more sincere or intensely-held attitudes, or they could reflect stylistic differences (such as verbosity), or they could reflect ambivalence. By the same token, intensely-held attitudes can often be expressed very succinctly. For example, respondents who like or dislike the parties' stances on abortion often write very short responses, and tend to have some of the most stable responses.

Beyond this, on the inference side, if a response is extremely short – and many of them are – it can sometimes be very difficult to interpret the response at all, much less infer the respondent's underlying attitude. And, in scoring documents with our method, we are able to average more word scores when a document is longer, likely increasing the reliability of our estimate (whether or not the underlying attitude is more intense and consistent) – even though the detailed, longer responses can be problematic when using unsupervised *training* to *find* attitude dimensions to score words on.

On the other hand, longer responses could contain a larger number of uninformative, filler words, even when the response as a whole can be clearly placed on a dimension.

To try to rule out some of these possibilities, we tested whether respondents who wrote longer documents in the 1st wave of 2 had higher test-retest reliability than shorter ones. These results are shown in Figure J.1. In this, we did not find that response length was consistently associated with more stability one way or the other.

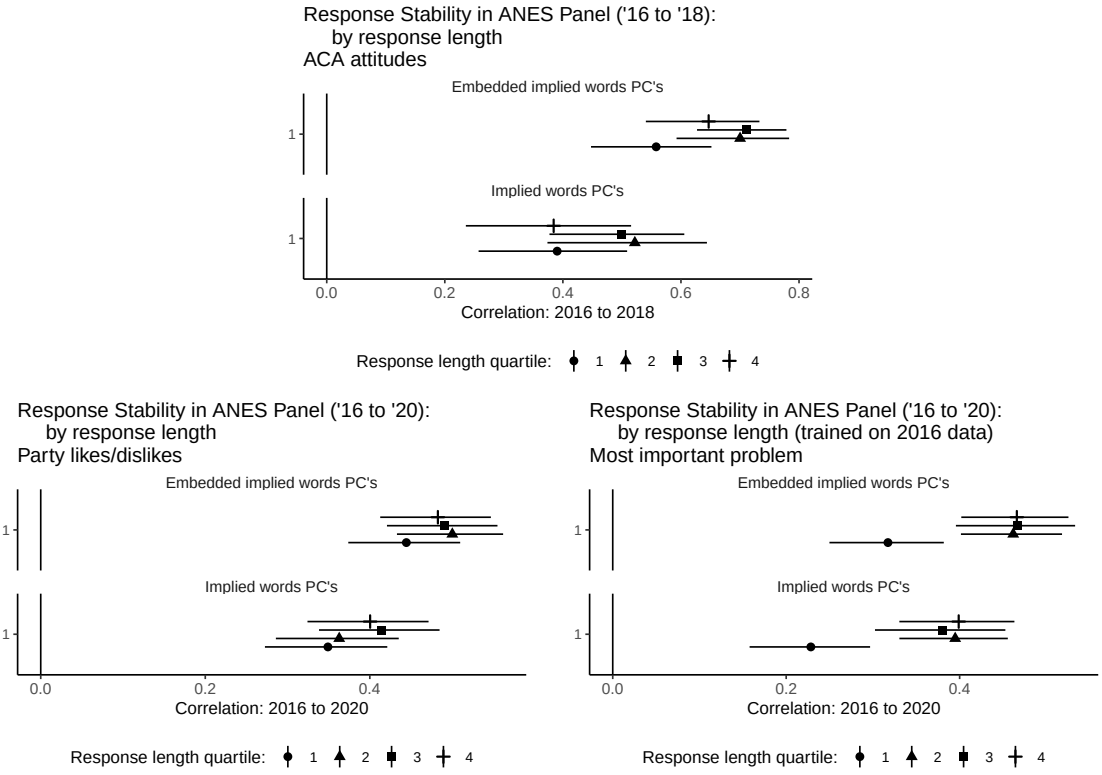


Figure J.1: *Test-retest reliability by response length quartile.* By and large, test-retest reliability was not different for the implied word scores across different quartiles of document lengths (as measured in the first wave of each comparison to avoid dropping respondents who wrote longer answers in one wave or the other). However, in the most important problem data, we do observe a very large difference between the first quartile of responses (very short responses) compared to the longer responses. In these analyses, we use the 2016-2020 ANES waves because they are much larger, and so we can split the data into quartiles without creating very small bins.

K Example responses and scores

First dimension in sd's	First dimension (embedded score) in sd's	Open-ended response, first 50 words stopwords and words <= 2 characters in gray were removed from the document-term matrix but not the embedded text
1.40	2.11	they're more for the people they try to help out the people the middle class
1.76	2.06	they're for the rich people
1.76	2.03	they are more for the rich people
0.59	1.47	i definetly feel they are the party of the working man basically more willing to give more money for the well being of children and people who arin more need of support both physcally and mentally
0.96	1.40	they try to do the best for the people have more help programs for people in us such as wefare aid to the underprivileged like food stamps and such
2.31	1.06	more for the rich
-1.11	0.90	they historical support and represent my values for me and most of us i believe they serve me and most of us better than republicians
0.69	0.89	they spend too much money don't know if it's the democrats raising federal employee wages or not they spend too much money to get voted in
0.70	0.70	i don't like richard nixon that still hangs in my mind lack of honesty republicans hold back can't tell if reagan is sincere
2.00	0.34	i'm a democrat because my mama and daddy was a democrat
0.72	0.14	it seems as though we always have wars and we have our wars when they are in power but maybe i'm wrong on that
0.56	-0.22	everything
-0.60	-0.59	it is a conservative thinking party weigh their problems and maintained a good relationship with foreign countries their import export policies are good the development plan for our country are good developing oil minerals science hope he balances the budget
0.00	-0.71	almost everything
-1.38	-0.87	the conservative ideas i like they are pro business and anti tax
-0.40	-1.05	their stand on a lot of issues that affect people not just working but personally gun control the general way they think we ought to be
-2.15	-1.08	they stand for family and moral values
-0.20	-1.32	i'm fairly conservative so i like the fact that they would not pass a law to let a woman walk around naked or show it on tv i wouldn't object to two people of the same sex who want to be partners but i don't think they should be allowed ... [truncated for this table]
-3.02	-2.17	same sex marriage support pro choice stem cell research support health care laws
-2.67	-2.46	they support abortion
-1.95	-2.66	approach to some social problems overly strict on personal rights like abortion

Table K.1: Example party likes/dislikes responses: randomly sampled by bin (cutoffs at ± 0.5, 1, 2) and ordered by first dimension of embedded implied word method. We have added dashed lines at 1 and -1 standard deviations of the scores. These redacted responses are no longer restricted use data: `https://electionstudies.org/data-center/restricted-data-access/`.

First dimension in sd's	First dimension (embedded score) in sd's	Open-ended response, first 50 words stopwords and words <= 2 characters in gray were removed from the document-term matrix but not the embedded text
3.16	1.12	they are crooks too they're all the same
2.14	1.90	they're more for the rich than the poor
2.06	1.92	they are more for the poor man
1.39	1.83	the raise the taxes for the low income and their not for the people with low income their for the richer people
1.35	1.75	they are out to help the middle classes and the poor
1.18	1.83	they are for the middle class every day people
0.84	-0.37	very much afraid that if mondale is elected we will end up in a war there always was a democratic president in office when we have gone to war
0.64	1.80	they like to make money for poor people they have jobs for poor people benefits healthcare
0.57	0.16	there are too many yes men in the demo party leave it at that
0.23	-0.37	seem to be a little more conservative they're conscious of budget spending money programs to save taxpayers money looking more at the deficit to balance the budget more aware of what's going on
-0.35	-0.29	not very unified
-0.38	-1.06	the way they have handled foreign relations
-0.51	-0.50	they are not humane enough
-0.94	-0.96	fore american people the economy business prolife freedom of speech
-0.99	-1.15	the way they handle the economy lower taxes more moderate in beliefs support 2nd ammendment
-1.04	-0.75	i think it's more respectful of individual rights abortion gay rights it demonstrates a belief that govt can do good in ways other than shoveling potholes the peace corps making more money for supporting college students i think it's more inclusive especially across racial lines
-1.30	-2.18	general conservatism stand on abortion era and defense spending a strong defense they aren't as willing to spend money
-1.75	-2.56	on some issues they're too liberal for me like abortion
-2.07	-2.61	mostly pro abortion or woman's choice
-2.30	-1.91	conservative values
-2.43	-2.34	i don't care for their stance on abortion gun control welfare

Table K.2: Example party likes/dislikes responses: randomly sampled by bin (cutoffs at ± 0.5, 1, 2) and ordered by first dimension of non-embedded (document-term matrix only) implied word method. We have added dashed lines at 1 and -1 standard deviations of the scores.

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