CDC Study Text Analysis:

Findings and Figures

**Model Comparisons**

**Figure 1**

*Structural Topic Modeling Summary*

Figures to include in final table:

* Diagnostic table
* Bar chart for best solution
* Example documents visual
* Expected topic proportions
* Estimated effect plot for a select relationship b/w a topic and a global motive

**Review Figures and Tables for 2, 3, and 4-Topic Model Solutions on Reasons For**

**Figure 1**

*Model Comparison on Fit Statistics for Reasons For*

Diagram, shape, engineering drawing, polygon

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*Note*: y-axis in ascending; 0 suggests total semantic coherence; 10 suggests total exclusivity of topics; higher residual values may indicate more topics needed to account for variance

**Table 1**

*Model Comparison on Fit Statistics for Reasons For*

|  |  |  |  |
| --- | --- | --- | --- |
|  | **2-Topic Solution** | **3-Topic Solution** | **4-Topic Solution** |
| Semantic Coherence | -238.04 | -254.52 | -246.38 |
| Exclusivity | 7.53 | 8.45 | 8.87 |
| Held-Out | -4.90 | -4.78 | -4.62 |
| Residual | 3.40 | 2.84 | 2.75 |

*Note*: 0 suggests total semantic coherence; 10 suggests total exclusivity of topics; higher residual values may indicate more topics needed to account for variance

2-Topic Solution

Graphical user interface, text, application, email

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Chart, bar chart, funnel chart

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Chart

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3-Topic Solution

Graphical user interface, text, application, email

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Chart

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Chart, waterfall chart

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4-Topic Solution

Graphical user interface, text, application, letter, email

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Chart, bar chart

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Chart

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II. Model Comparisons for Reasons Against Data

**Figure 2**

*Model Comparison on Fit Statistics for Reasons Against*

Diagram

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*Note*: y-axis in ascending; 0 suggests total semantic coherence; 10 suggests total exclusivity of topics; higher residual values may indicate more topics needed to account for variance

**Table 2**

*Model Comparison on Fit Statistics for Reasons Against*

|  |  |  |  |
| --- | --- | --- | --- |
|  | **2-Topic Solution** | **3-Topic Solution** | **4-Topic Solution** |
| Semantic Coherence | -219.61 | -226.16 | -238.74 |
| Exclusivity | 8.10 | 9.00 | 8.94 |
| Held-Out | -4.98 | -5.00 | -5.07 |
| Residual | 2.72 | 2.42 | 2.10 |

*Note*: 0 suggests total semantic coherence; 10 suggests total exclusivity of topics; higher residual values may indicate more topics needed to account for variance

Reasons Against – 2-Topic Solution

Reasons Against – 3-Topic Solution

Reasons Against – 4-Topic Solution

**Notes for data demonstration on 12/17**

Context on the topic modeling framework used:

Structural Topic Model (‘STM’) is topic modeling algorithm that is used to identify latent topics within a large corpus of text data (Roberts et al., 2019). Topic models are often referred to as ‘unsupervised’ machine learning methods because they infer underlying content rather than assume (Roberts et al., 2014).

STM generates topic model solutions based on document-topic and topic-word distributions. Specifically, as Roberts et al. (2019) explain, “A topic is defined as mixture over words where each word has a probability of belonging to a topic. And a document is a mixture over topics, meaning that a single document can be composed of multiple topics. As such, the sum of topic proportions across all topics for a document is one, and the sum of the word probabilities for given topic is one”.

In this study, we follow steps for estimating and evaluating a structural topic outlined by Roberts et al. (2019). In our data, each participants’ reason stated is treated as a document in which the STM algorithm generates a topic model for all reasoning data based on words and their co-occurrences used by participants, and then by clustering word groupings (e.g. topics) that best describe the reasons participants stated. That is, by accounting for word frequency and the distance between words used in the participants’ stated reasons, the topic model infers the topics that are expressed in the reasoning data. In addition, one advantage of structural topic models, unlike other topic models (Blei et al., 2003), is that STM is able to account for covariates in the broader data set in which the text was generated that may be of interest to a researcher. Specifically, covariates that a researcher believes may account for the frequency of word use or content focus can be controlled for with STM. As an example, in a study of employee sentiment, if one believed that employees in the finance department were more likely than other to discuss… then including

**Mixed-Membership Model – Background**

* In mixed-membership model, each word in a given document (e.g. reason stated) belongs to exactly one topic
* The model determines what proportion of the document is represented by the topics present
  + Each document represented as a vector of proportions that denote what fraction of the words belong to each topic (Roberts et al., 2014)
* By contrast, in single-membership models, each document is restricted to only having one topic; which may be an unrealistic assumption considering how content is expressed in documents (e.g. a book can have many topics)

**Reasons For Data**

The following figures and tables represent outcomes derived from a 3-topic solution. The following graphics are the pieces of evidence that we would use as a team to decide which topic model solution to use. Deciding between topic model solutions is both a subjective and objective (e.g. fit statistics) process. My goal in this write up was to present a sample of the most commonly used pieces of information that researchers use to evaluate topic model fit. What we will do is compare the following 3-topic solution with alternative models; say 2, 4, and 5-topic models. Through subjective and data-driven evaluation, we ultimately build a case for the best possible representation of the latent constructs that we believe are in the sample data.

**Figure 1**

*Highest Word Probabilities for Each Topic in Reasons For Decision*

Chart, bar chart

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Figure 1 shows the words that are most common in each of the 3 topics identified by this model. This graphic is a good way to subjectively assess whether the model output is semantically meaningful, which is to say, do these word groupings meaningfully represent separate latent constructs?

**Figure 2**

*Diagnostic Values by Number of Topics*

Diagram, engineering drawing

Description automatically generated

Figure 2 presents common metrics for selecting and evaluating the best topic models from a data-driven perspective. This step is similar to a scree plot in EFA. To generate these plots, the diagnostic metrics were calculated for topic models that were fit ranging from k = 2 to k = 10 topics. One important metric is semantic coherence, which is a measure of quality within topics. Specifically, semantic coherence is maximized when a topic model converges on a solution in which high probability works for a topic tend to naturally co-occur in the documents that the model is fed (Mimno et al., 2011). We can see in Figure 2 that semantic coherence is best at k = 2 and worse at k = 10. Held-out likelihood represents how well each model represents words in the documents, where lower values for held-out likelihood are preferred. The same number of recommended topics is given with regards to held-out likelihood.

**Figure 3**

*Expected Frequency of Topic Occurrence Across Participants’ Reasons*

Chart, scatter chart

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Chart

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Moving on with the three topic solution, there are a host of follow up analyses that are run to iteratively evaluate the goodness-of-fit of the 3-topic model. Figure 3 shows the expected frequency of an identified latent topic in the data set. For our study, this means that topic 2, which may have something to do with keeping safe and healthy (more on this later), is expected to occur around 35% of the time in our sample data.

**Figure 4**

*Words Associated with Topics Related to Reasons For Decision by Fit Metric*

Graphical user interface, text

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Figure 4 is similar to the histogram in Figure 1 in that the words most associated with a given topic are shown. However, this figure also shows the most common words for a given topic when conditioning on a specific fit criteria. For example, in the figure, ‘marginal FREX’ weights words by their overall frequency andd how exclusive they are to the topic, therefore giving higher weights to words that appear less frequently in other topics (Roberts et al., 2019)

**Table 1**

*Correlation Between Topics*

A picture containing text, scoreboard

Description automatically generated

Correlations between topics are presented in Table 1. Positive correlations indicate that both topics are likely to be discussed within a document (Roberts et al., 2019). Notice, the strong negative correlations. This is a good sign in assessing the overall fit of the 3-topic solution as we would expect that topics would not co-occur too frequently in one participant reason. The reasons that participants state are short, so it is less likely that two or more constructs were expressed in participants’ reasons.

**Figure 5**

*Estimated Effects of Topics Related to Reasons For Decision on Attitudes*

Text

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Figure 5 shows the estimated relationship between participants’ attitudes and the latent topics identified by the 3-topic model solution. STM allows for inferences between topics and covariates to be expressed in a regression framework (Roberts et al., 2014). There are two main relationships between latent topics and covariates that can be tested with the regression framework that the STM package enables; prevalence and word use.

**Estimating Prevalence Conditioning on Covariate**

First, a researcher could explore whether is a relationship between a given covariate and the frequency with which a topic is expressed. To test this relationship, the researcher’s null hypothesis would be

HO: ( E[Topici ] | Attitude) = 0

Ha: ( E[Topici ] | Attitude) ≠ 0

**Figure 6**

*Estimated Proportion of Topic 3 Reason Stated for Level of Attitude*

Chart, line chart

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Results in Figure 6 revealed that the proportion of Topic 3 stated in reasons for the decision were positively related to participants’ attitudes towards CDC compliance behaviors.

**Estimating Word Use Conditioning on Covariate**

Additionally, using a regression framework applied to a structural topic model solution, a researcher can also test whether

By developing a regression equation in which we test the null hypothesis that covariate X has no relationship to either the a) frequency with which Topici occurs, or b) the

**Figures 6 – 8**

*Estimated Reasons For Topic Proportion for Level of Participant Attitude*

Chart, line chart

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Note: Participant attitude\_ave is plotted on the x-axis; y-axis represents expected proportion of Topic 1; These graphs show the estimated proportion of a topic occurring across all reasons stated for a given level of attitude. In the first graph, we see that the likelihood of Topic 1 occurring goes down as attitude towards decision goes up.

Chart, line chart

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Chart, line chart

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**Reasons Against Data**

In parallel to the evaluation and initial analyses above, the figures below were generated to assess a 3-topic model solution for the *reasons against* data.

**Figure 9**

*Highest Word Probabilities for Each Topic in Reasons Against Decision*

Chart, bar chart

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Table

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**Figure 10**

*Words Associated with Topics Related to Reasons Against Decision by Fit Metric*

Text

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**Figure 11**

*Estimated Effects of Topics Related to Reasons Against Decision on Attitudes*

Text

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**Figure 12**

*Estimated Reasons Against Topic Proportion for Level of Participant Attitude*

Chart, line chart

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A picture containing table

Description automatically generated

Text

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(Elmore, 2019)

**References**

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