

# Understanding the Role of Trust during COVID-19: A Time Series Analysis

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## Introduction

Existing long-term forecasting models for the pandemic struggle when predicting 3+ weeks ahead.

Indicators, such as mask usage and transportation patterns, are integral to the decision-making process of a population and holds importance in accurate forecasting.

### 2023 Summer Research

**Research Question:** For the state of California, what is the relationship between:

- Epidemiological outcomes - e.g. hospitalizations
- Trust in intervention - e.g. mask use
- Perception of risk - e.g. reason for vaccine hesitancy
- Source of trust - e.g. government

**Methods:** Lagged Correlation, Dynamic Time Warping (DTW), Dynamic Time Warping + Shapes (DTW+S)

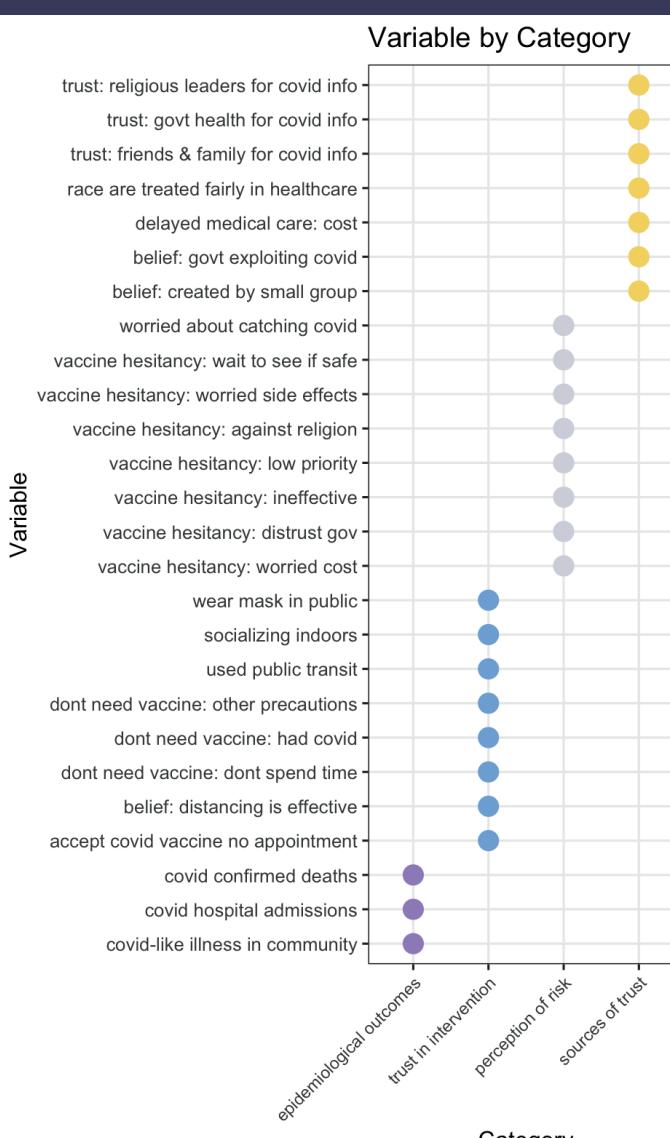
**Findings:** For the state of California, DTW+S was able to capture trust in intervention and outcomes the best. DTW was the only one to capture the relationship between source of trust and epidemiological outcome.

## Research Question

For the state of Texas, in addition to California, what is the relationship between epidemiological outcomes, trust in intervention, perception of risk, and source of trust?

## Dataset

### Variables



### Data Sources

- Covid-19 Trends Impact Survey from Carnegie Mellon University's Delphi Group (CMU 2020).
- U.S. Department of Health & Human Services & Johns Hopkins University epidemiological variables were added.

### Data Cleaning

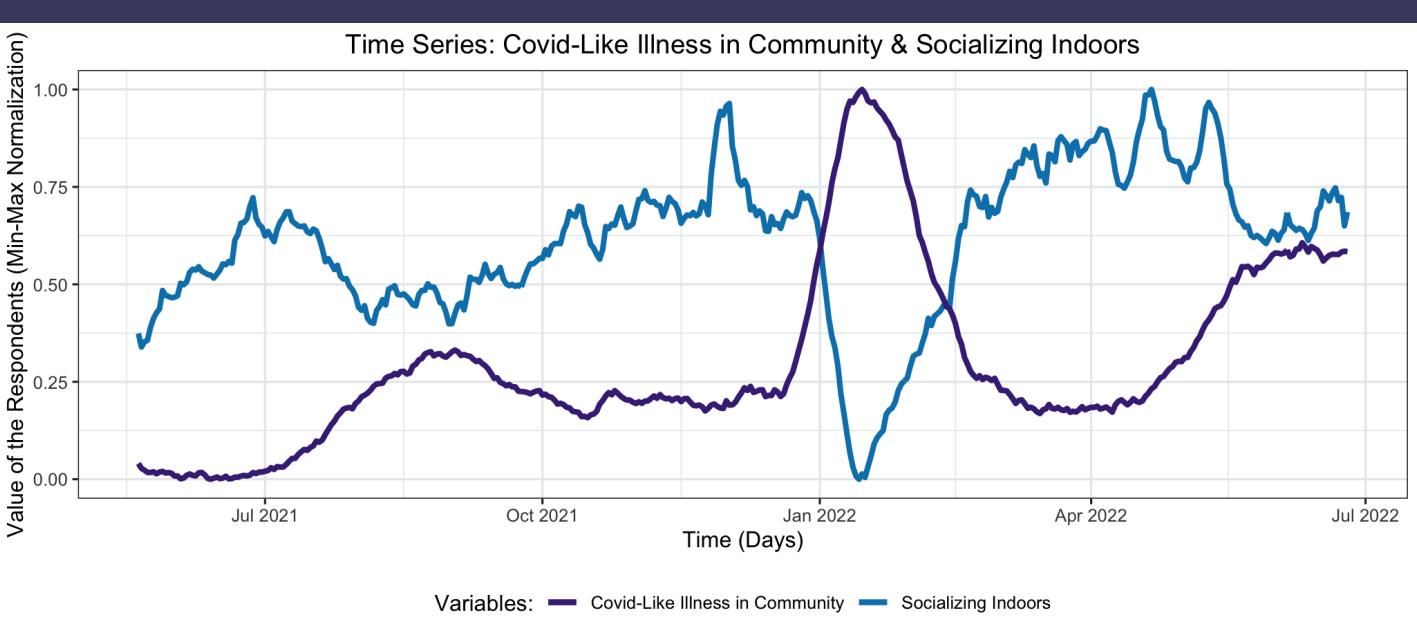
For each selected state (filtered):

- Variables:** 26 retained out of initial 511 variables -- columns
  - Added: Category
- Dates:** May 20, 2021 to June 25, 2022 (402 days) -- rows
- States:** California or Texas
- Values:** Independent min-max normalization

### Dataset

| time (days) | accept covid vaccine | believe created small group | believe distancing effective |
|-------------|----------------------|-----------------------------|------------------------------|
| 5/20/21     | 1                    | 0.466                       | 1                            |
| 5/21/21     | 0.962                | 0.131                       | 0.957                        |
| 5/22/21     | 0.818                | 0.158                       | 0.921                        |
| 5/23/21     | 0.757                | 0.287                       | 0.873                        |

## Methods

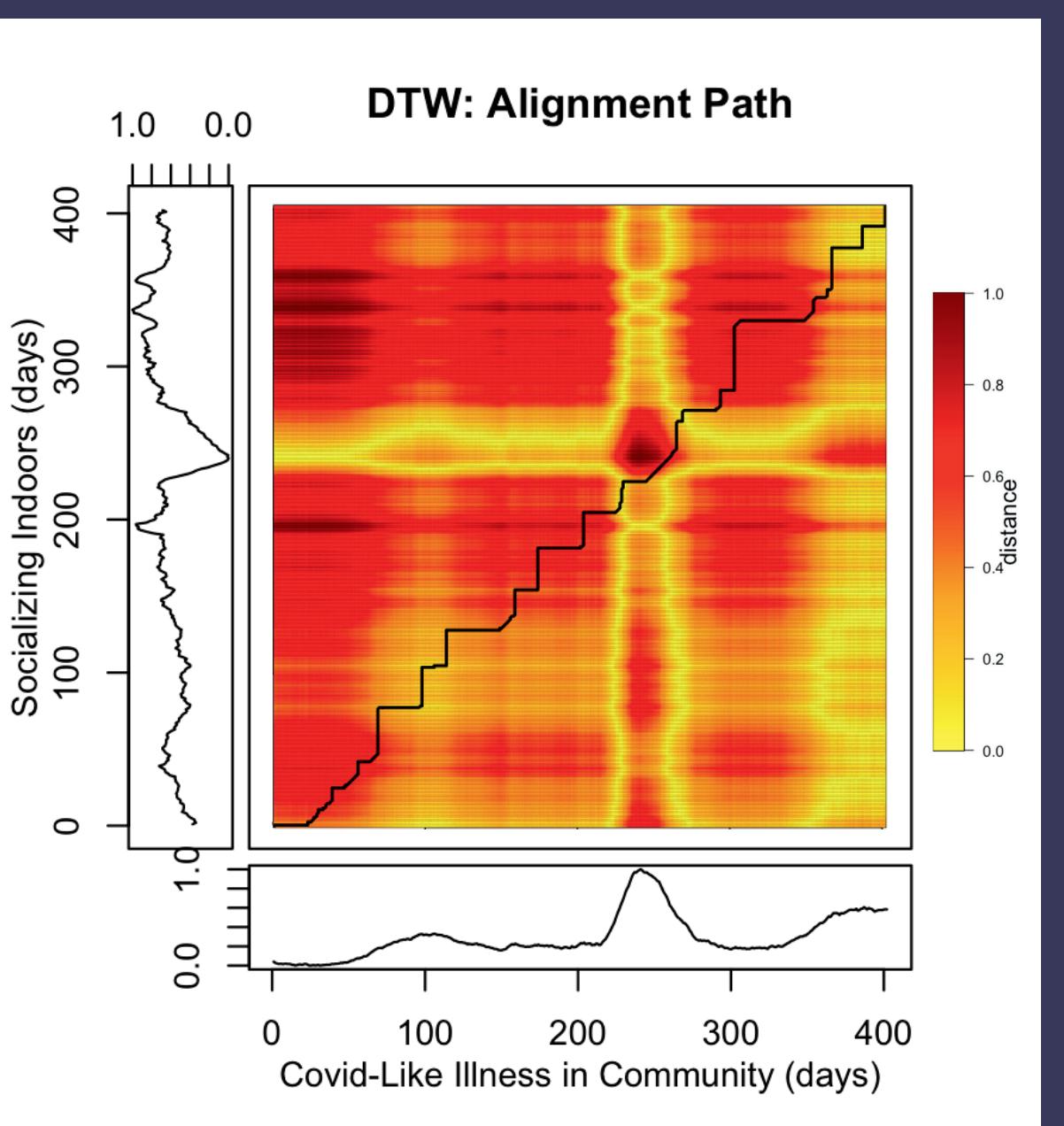


### Dynamic Time Warping

Produces optimal alignment between two dataset collected over time by locally stretching or compressing.

#### How it works for one example:

- Heat map:** Distance between the values from two different variables on each day.
- Alignment Path:** Optimal shortest distance between two variables.



#### 3. Output:

- Variable A doesn't predict Variable B, vice-versa
- Both produce same optimal distance & path

## Implementation

- Sakoe Chiba Window:
  - + 21 days
- Computes DTW for all 2 combinations out of the 26 variables
  - 325 relationships
- Considers Non-inverse and Inverse Relationships

## Output

- 26 X 26 Matrix
  - Inverse represented by (-)
- Undirected Network Graph
  - Filtered by threshold

Figures & Variable Definitions



## Results

### Epidemiological Outcomes

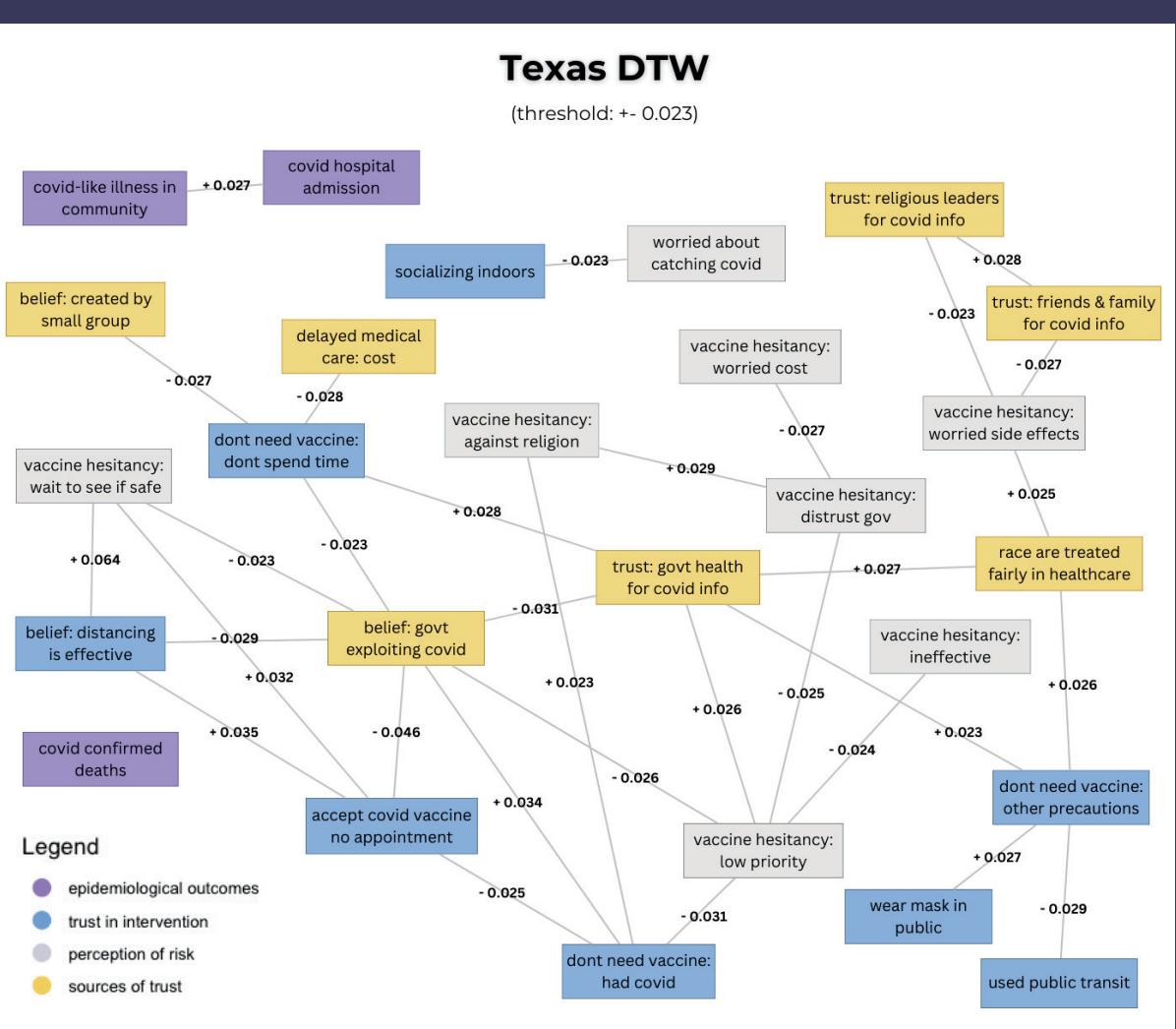
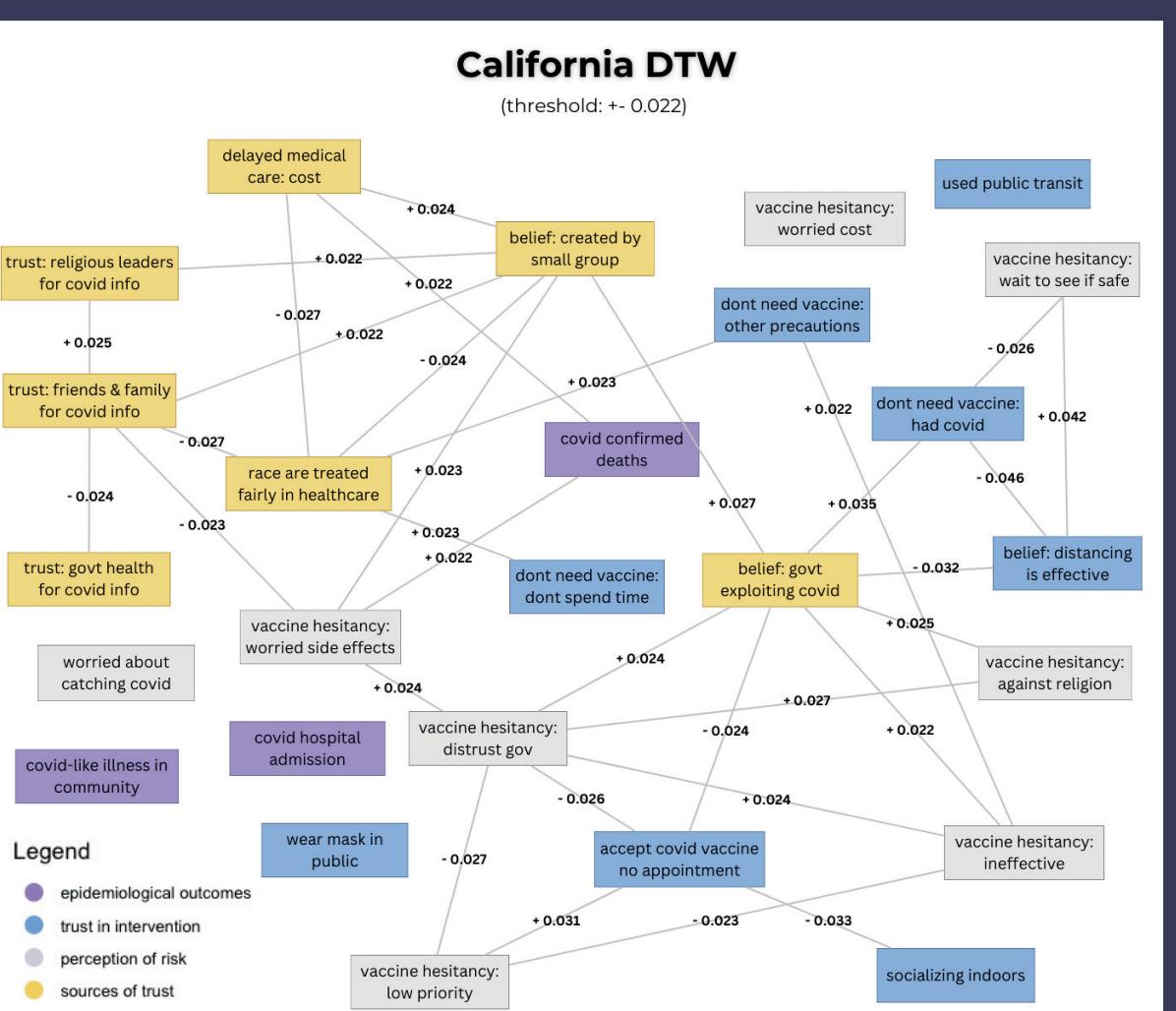
- CA:** Delaying medical care due to cost shows similar pattern to number of deaths due to COVID (+0.022). Shows critical role of financial barriers in healthcare access
- TX:** Sources of Trust has no relationships with outcomes

### Trust in Intervention

- BOTH:** Inverse relationship with believing the government is exploiting COVID and
  - believing that distancing is effective (CA = -0.032) (TX = -0.029)
  - accepting vaccine if offered (CA = -0.024) (TX = -0.046)
- BOTH:** Government exploitation and not needing the vaccine because already had COVID (CA = +0.035) (TX = +0.034).
- TX:** Trusting the government for health information has a relationship with not getting the vaccine by choosing to take precaution instead (+0.023).
  - Shows trust in the source (government) but not the intervention (vaccine).

### Perception of Risk

- BOTH:** Trusting friends & family for COVID info has an inverse relationship with hesitancy about vaccine side effects (CA = -0.023) (TX = -0.027).
- CA:** There is a positive relationship between hesitancy about getting a vaccine because of side effects and believing that COVID was created by a small group (+0.022).
- TX:** Trusting the government for health has a positive relationship with being hesitant to get the vaccine due to feeling others need it more (0.026).



### Source of Trust

- CA:** Inverse relationship between trusting friends & family and trusting government for COVID info (-0.024). Trust in friends also has a positive relationship with the belief that COVID was created by a small group (+0.022).
- BOTH:** Trust in COVID info from religious leaders has positive relationship with trust in info from friends & family (CA = +0.025) (TX = +0.028).

## Discussion

### Conclusion

- For CA, delayed medical care due to cost has a relationship with mortality trends, highlighting financial barriers to healthcare. However, this relationship was not found in TX.
- Who you trust, whether the govt, friends, family, religious leaders, has a relationship with your trust in intervention methods (e.g. believing distancing is effective) and vaccine hesitancy (e.g. side effects).
- Beliefs surrounding govt exploitation has negative emotions around accepting vaccine and reveals respondents' not needing the vaccine for other reasons (e.g. had COVID).
- For TX, surprisingly, even if you trust the govt, respondents still believe they don't need vaccine because they use other precautionary methods (e.g. masks), or because not with high risk people; there's trust in the source but no trust in the intervention.

### Limitations

- DTW --> General Interpretations:** Further research needed to make definitive claims on directionality (e.g. Is it hesitancy of vaccine that influences trust in govt or vice-versa?).
- DTW+S:** Captures more epi relationships (forecasting).
- Survey Population:** U.S., active Facebook user, 18+
- Non-Response Bias:** There might be unobserved reasons why someone would choose not to take the survey

## Acknowledgements

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## References

CMU Delphi Research Group (2020). Covid-19 Trends and Impact Survey. Delphi Epidata API. <https://cmudelphi.github.io/delphi-epidata/api/covidcast-signals/fb-survey.html#privacyrestrictions>.