

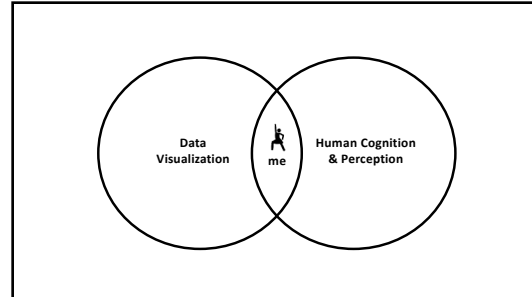
Designs to Support Better Visual Data Communication





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Cindy Xiong, Assistant Professor
UMass Amherst CICS

1



2

Xiong → 

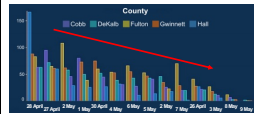
“shown/-tion”
visualization
visualizaXiong (Lab)
cogniXiong
percepXiong
human deciXiong-making

3

Design choices can lead to powerful and intuitive insights, or leave important patterns obscured and misunderstood.

4

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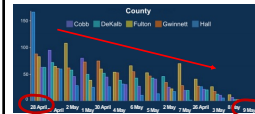


Misleading decreasing trend.

(Georgia Department of Public Health, 2020; Burns, Xiong, Cairn, Frazzetto & Mahow, 2020)

5

Design choices can lead to powerful and intuitive insights, or leave important patterns obscured and misunderstood.

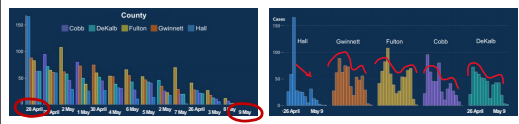


Notice which day had the most/least # of cases.

(Georgia Department of Public Health, 2020; Burns, Xiong, Cairn, Frazzetto & Mahow, 2020)

6

Design choices can lead to powerful and intuitive insights, or leave important patterns obscured and misunderstood.

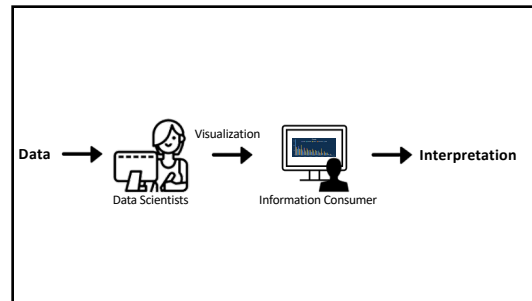


Notice which day had the most/least # of cases.

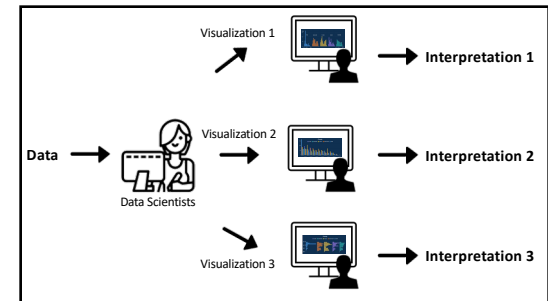
Notice the change in # of cases as time passes.

(Georgia Department of Public Health, 2020; Burns, Xiong, Cairn, Frazzetto & Mahow, 2020)

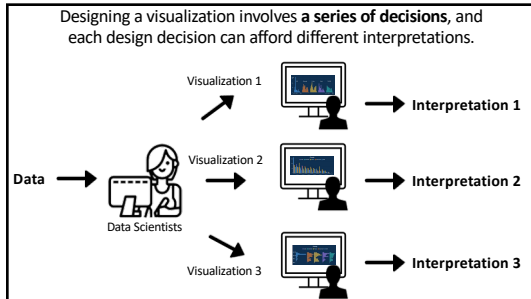
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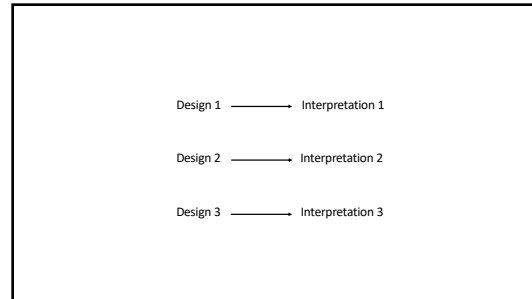
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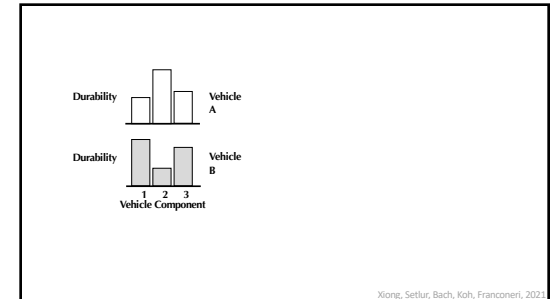
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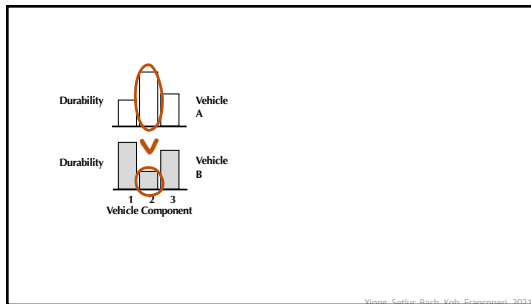
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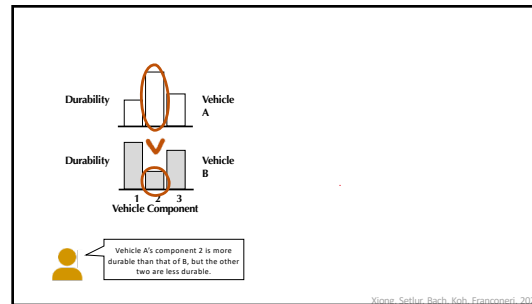
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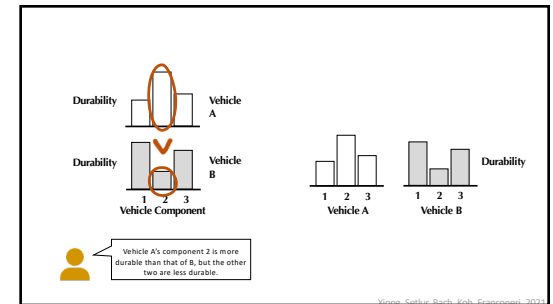
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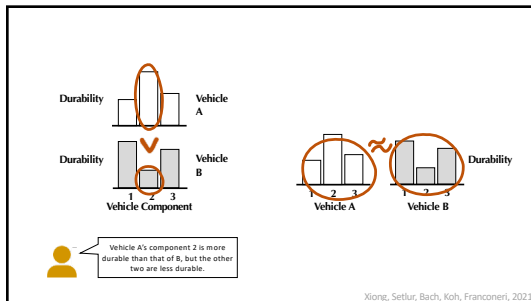
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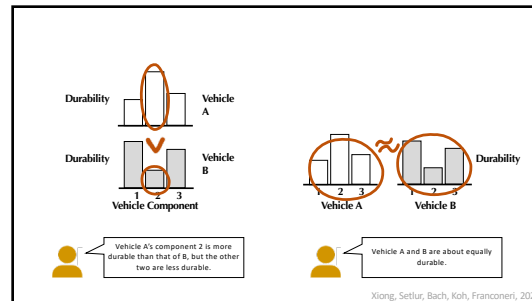
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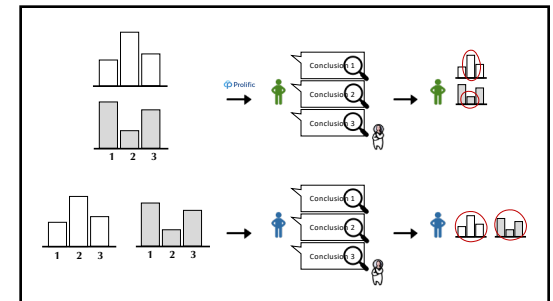
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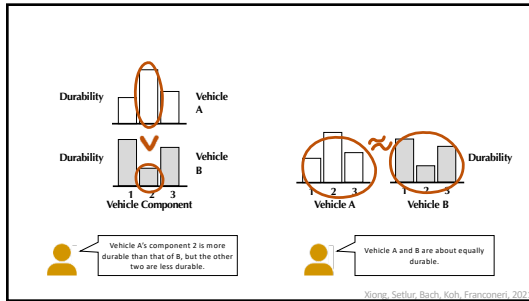
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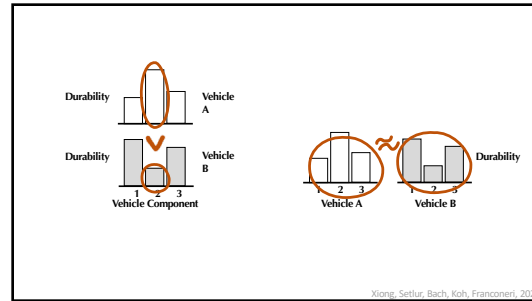
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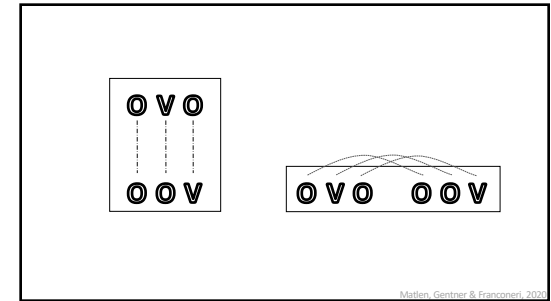
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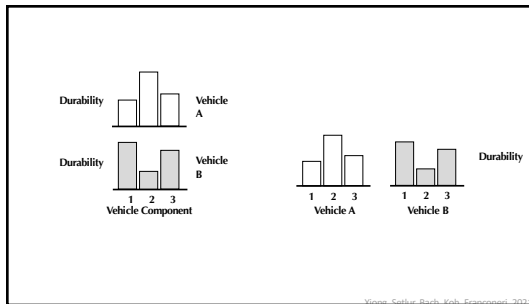
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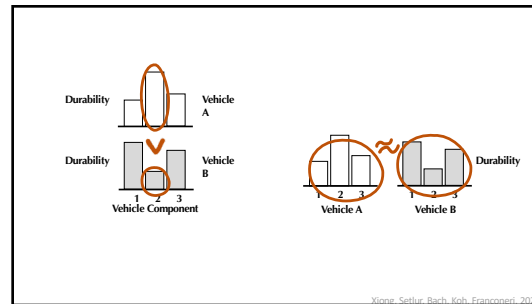
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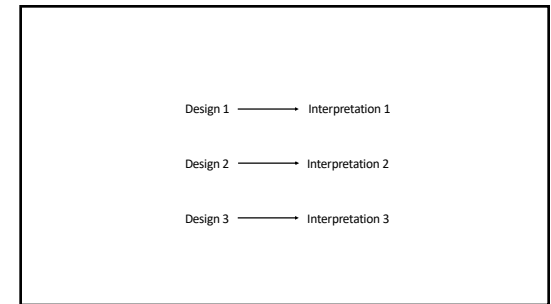
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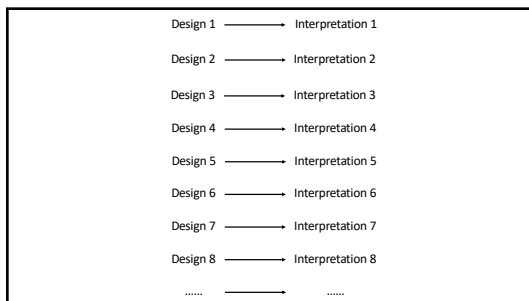
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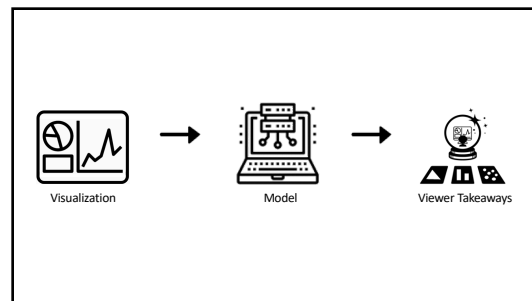
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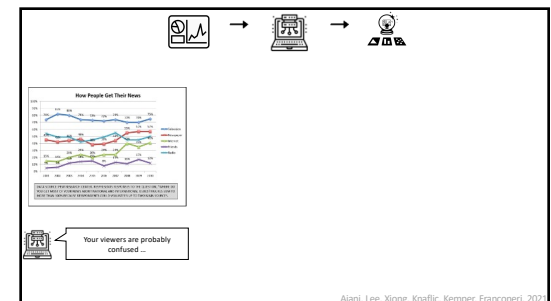
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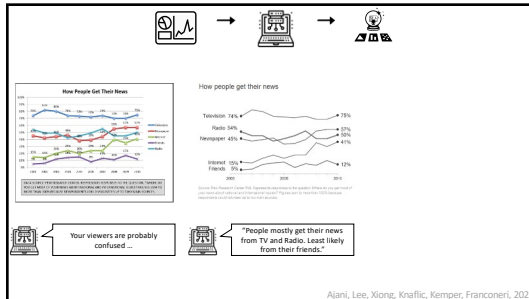
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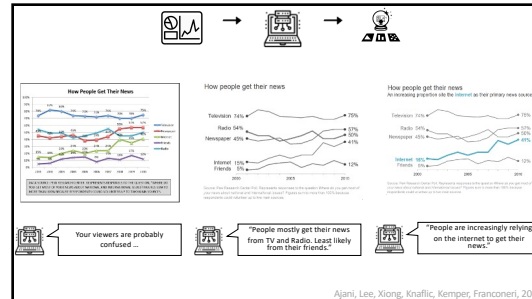
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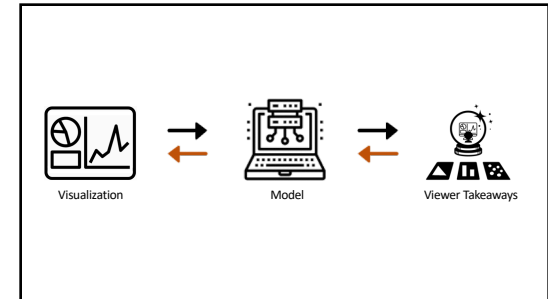
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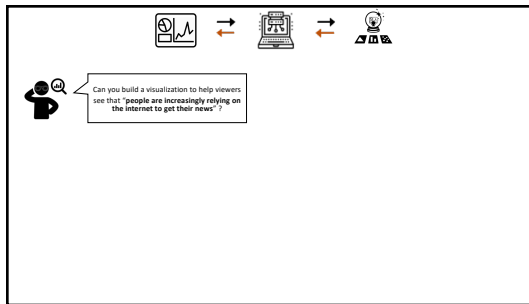
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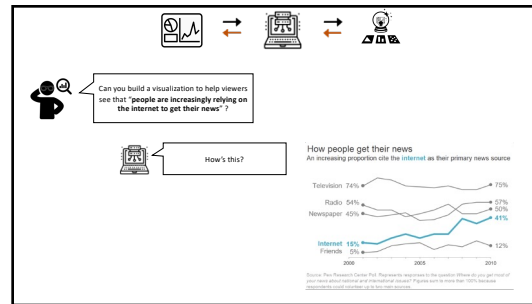
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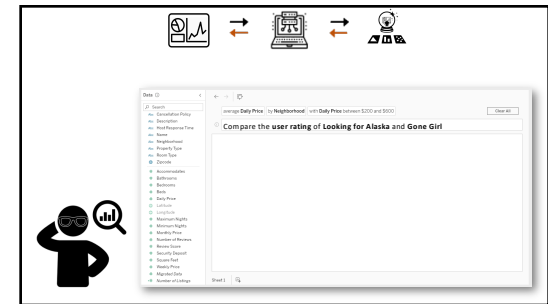
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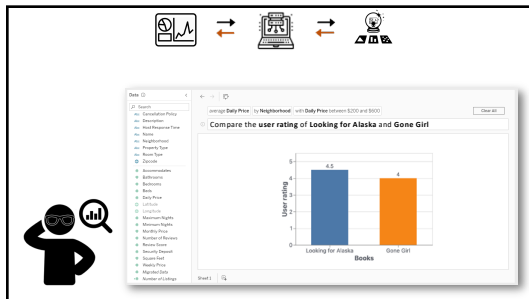
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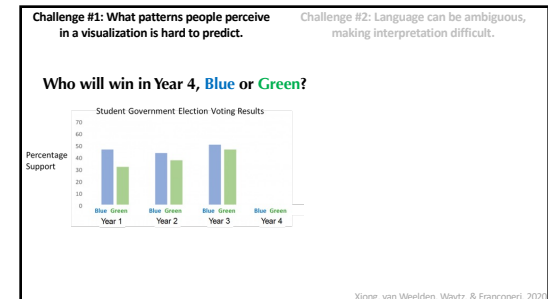


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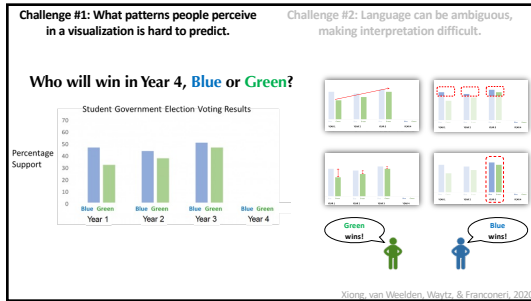
Challenge #1: What patterns people perceive in a visualization is hard to predict.

Challenge #2: Language can be ambiguous, making interpretation difficult.

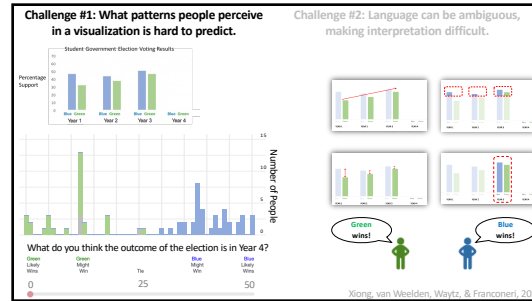
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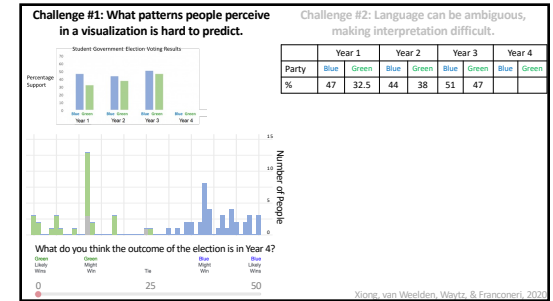
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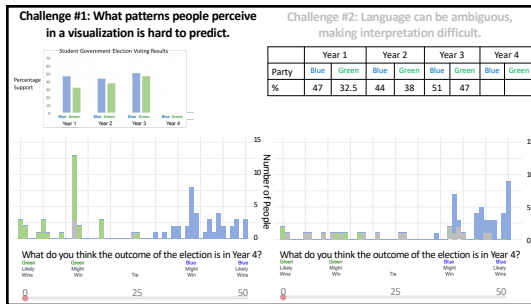
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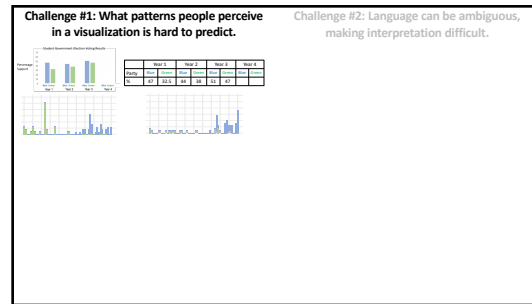
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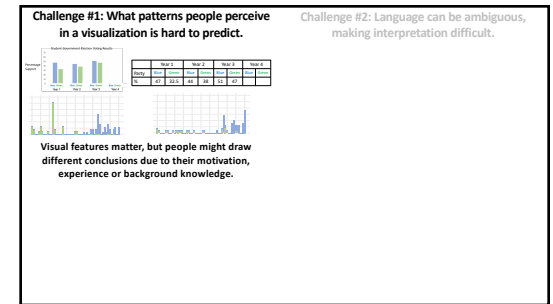
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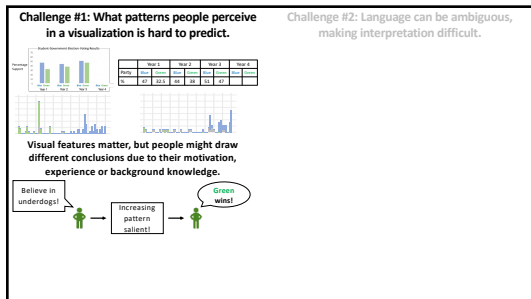
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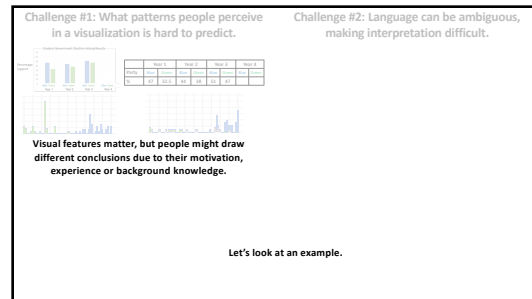
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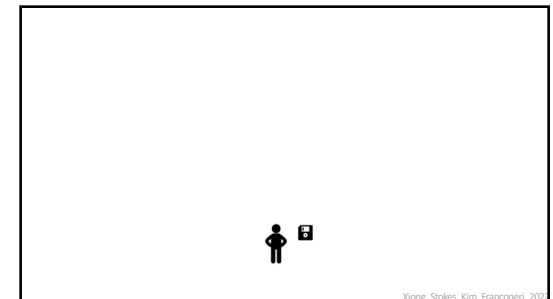
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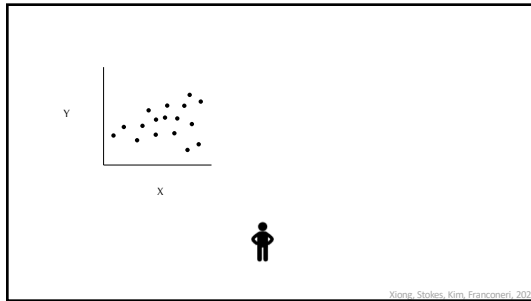
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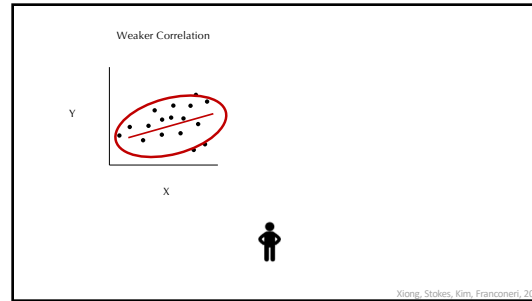
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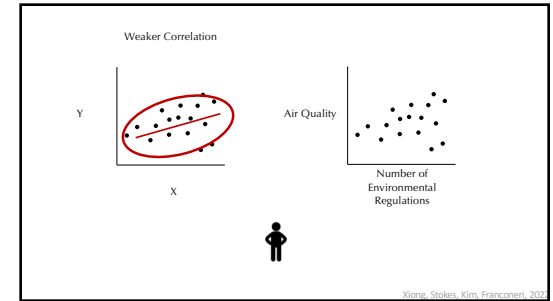
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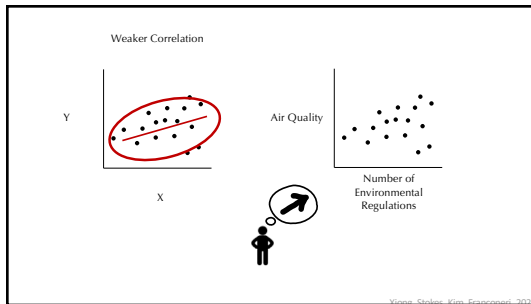
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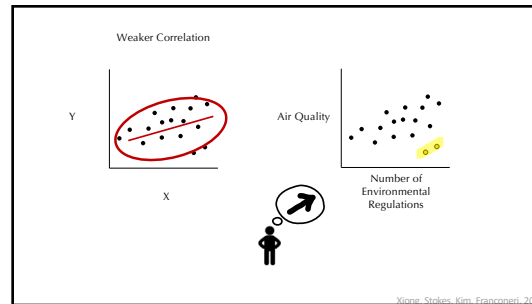
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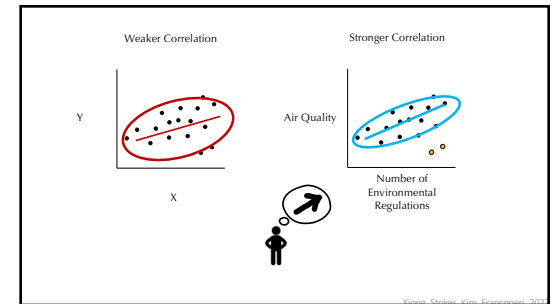
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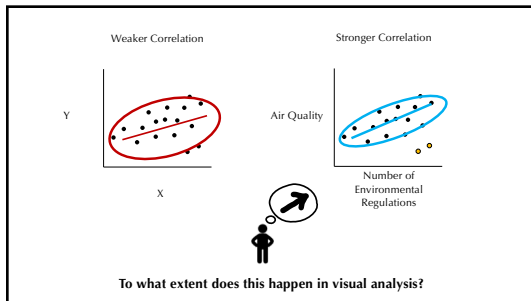
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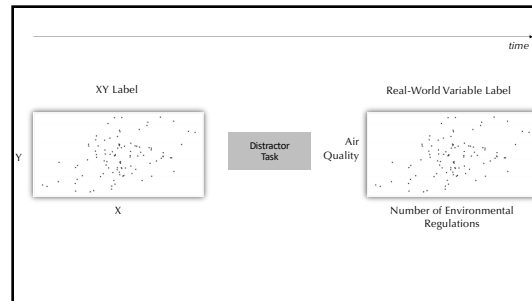
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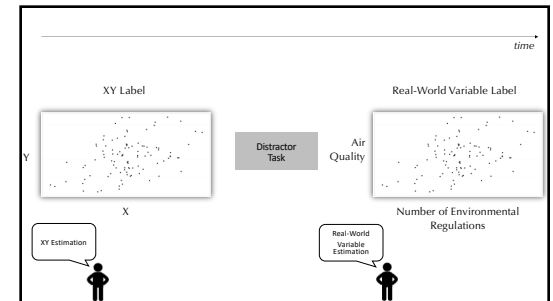
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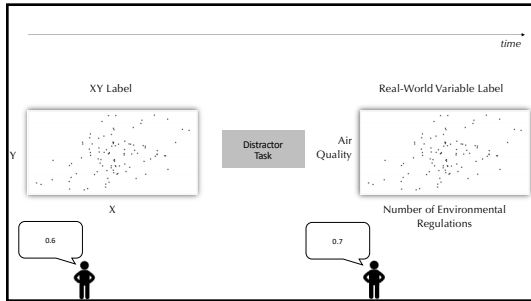
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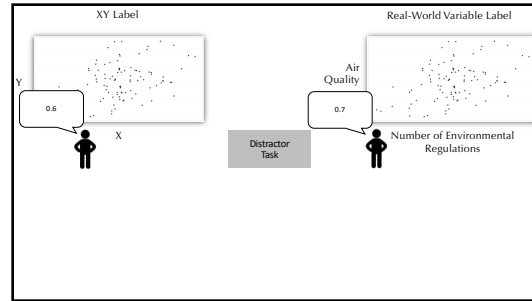
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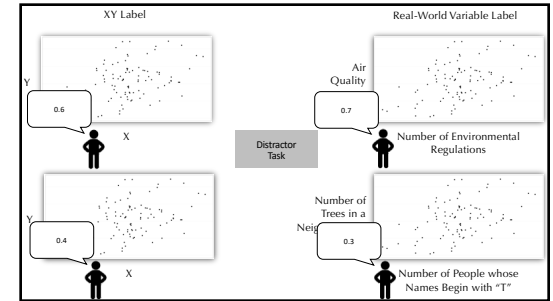
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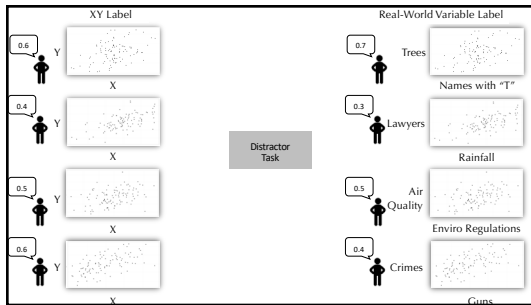
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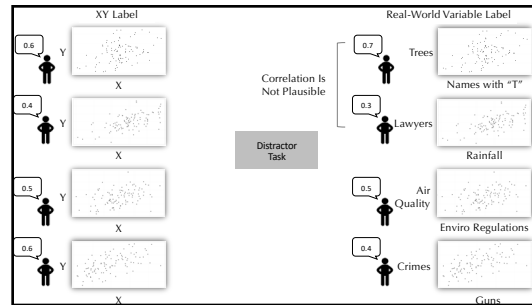
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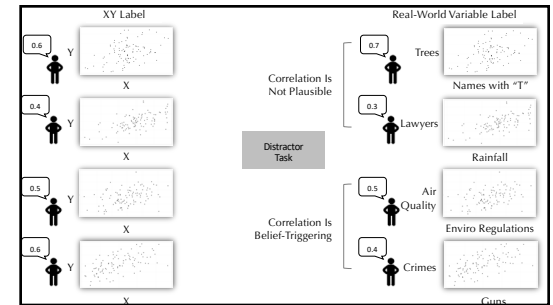
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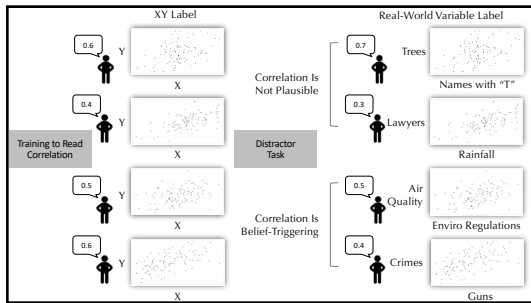
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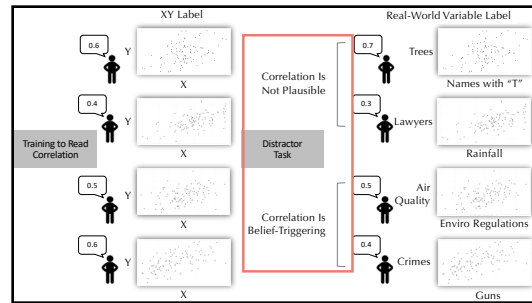
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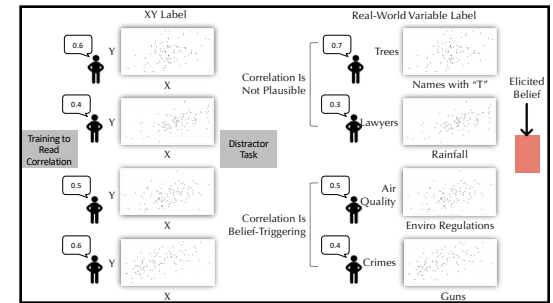
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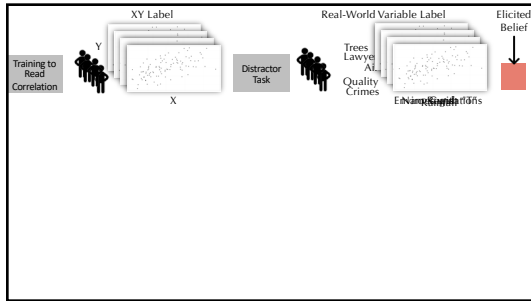
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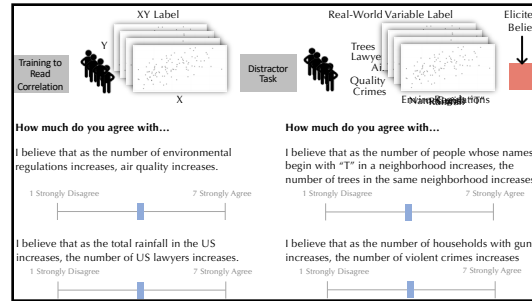
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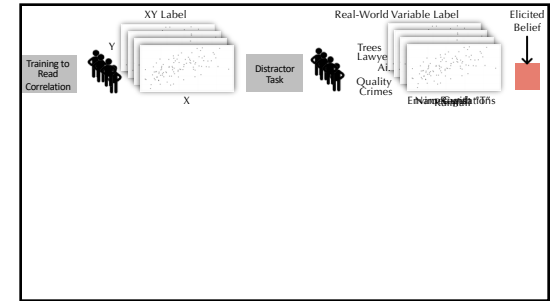
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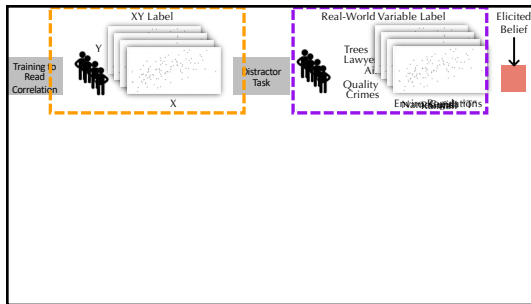
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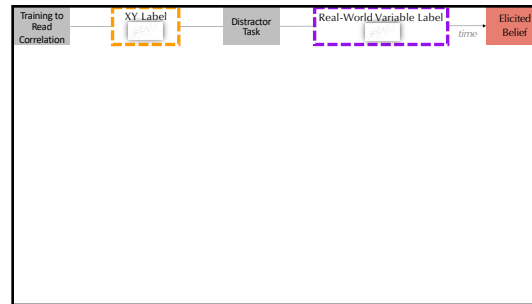
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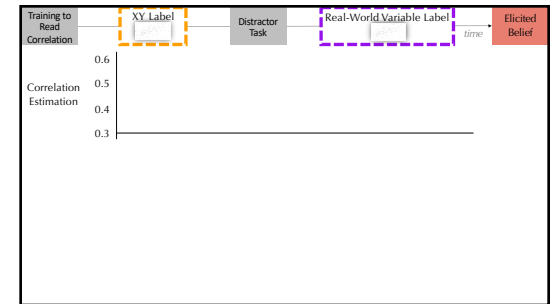
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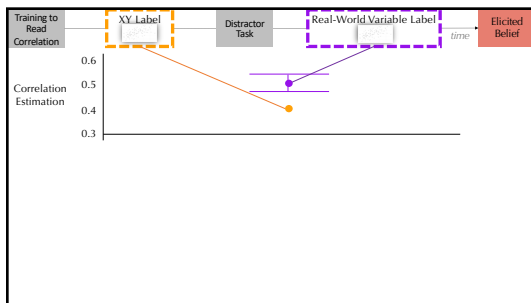
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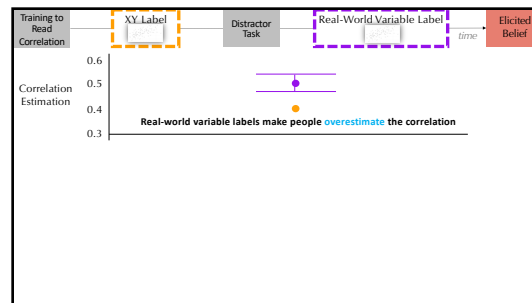
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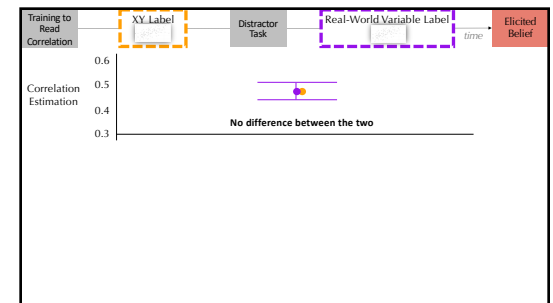
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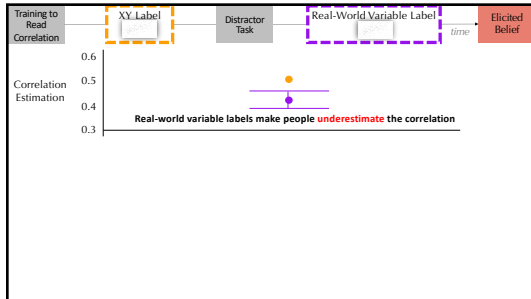
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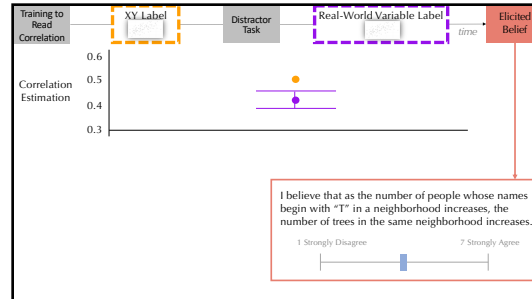
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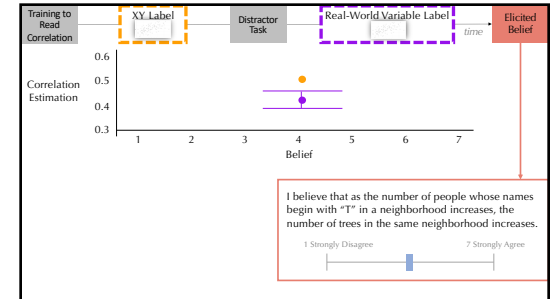
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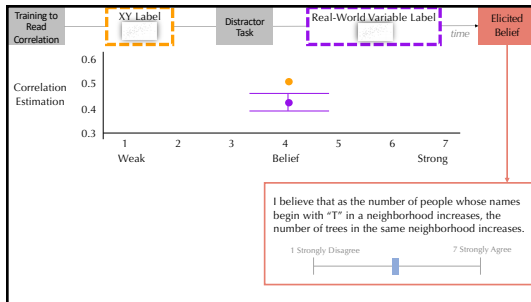
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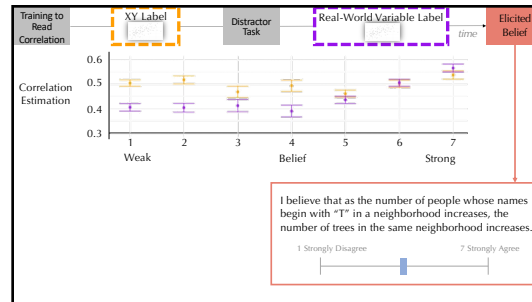
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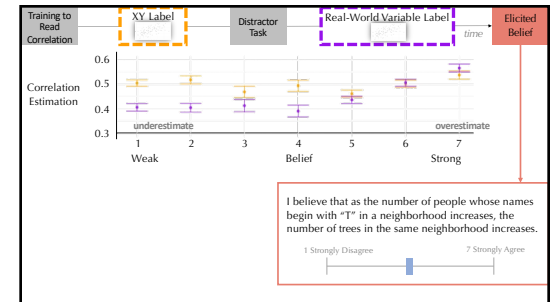
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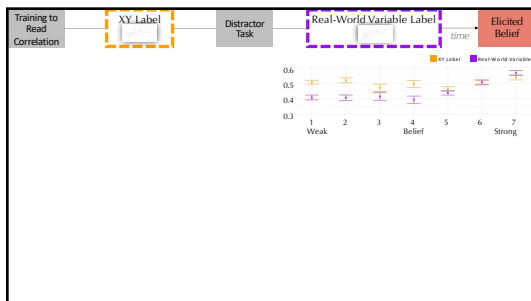
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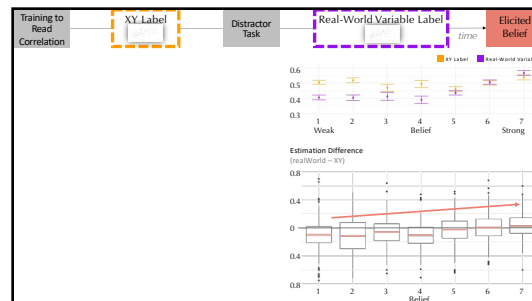
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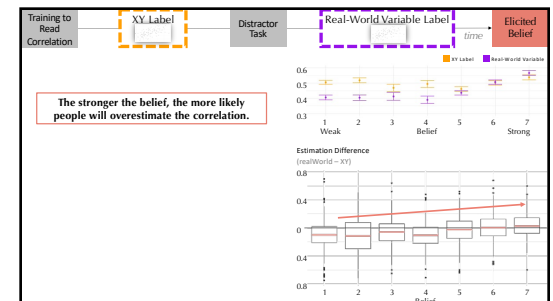
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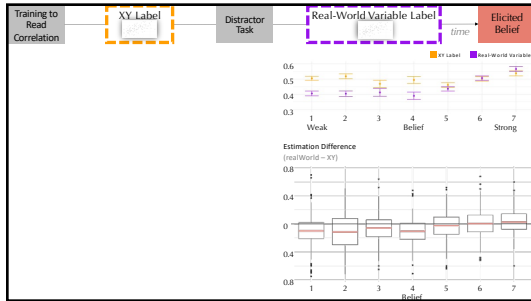
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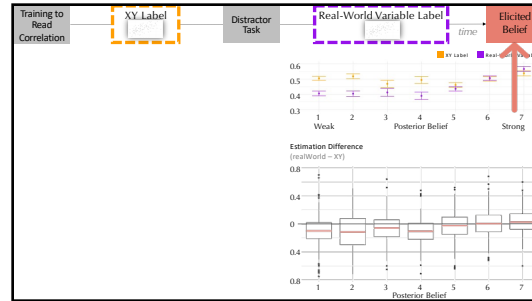
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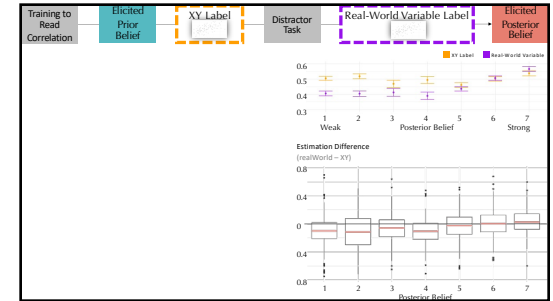
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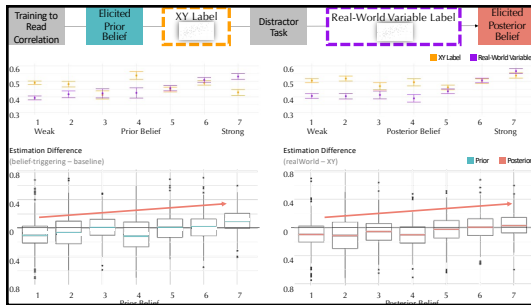
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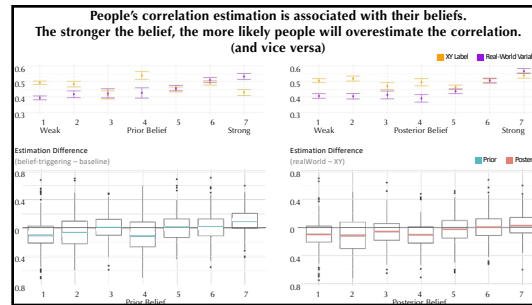
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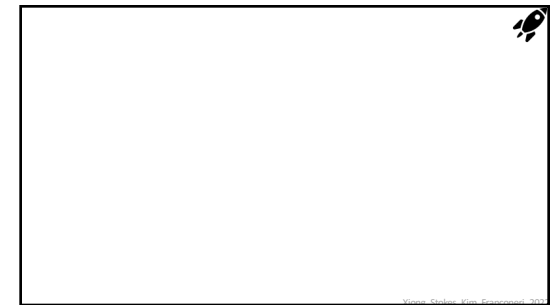
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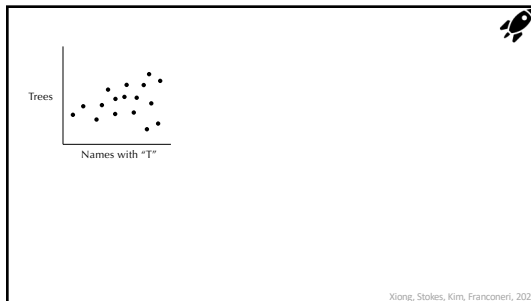
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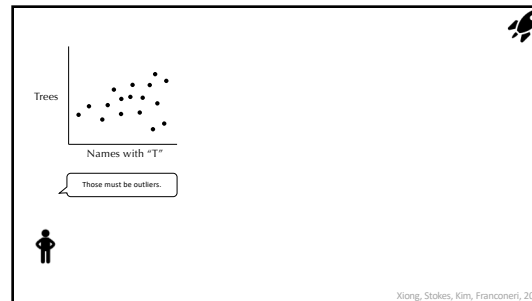
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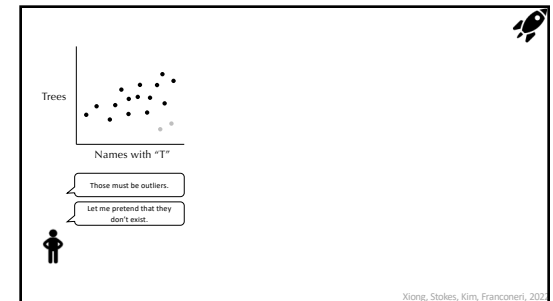
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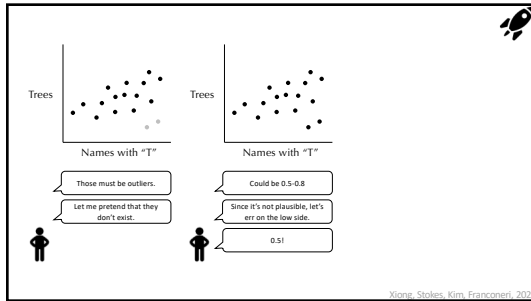
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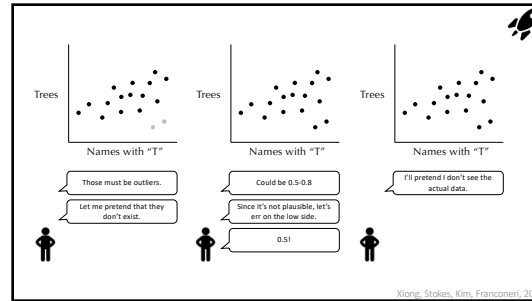
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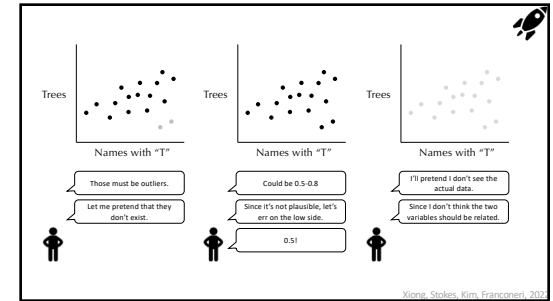
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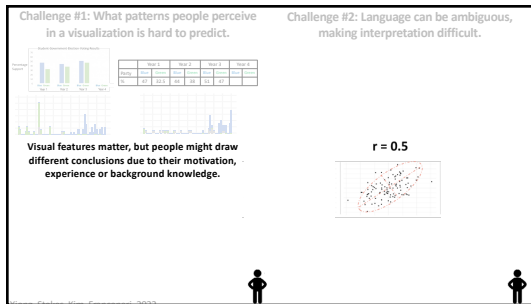
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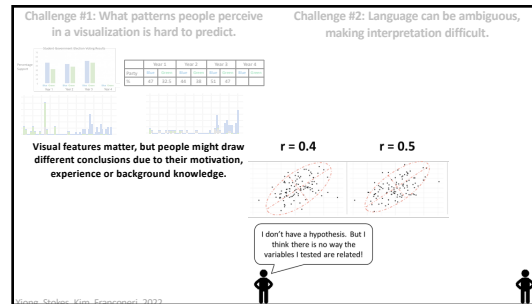
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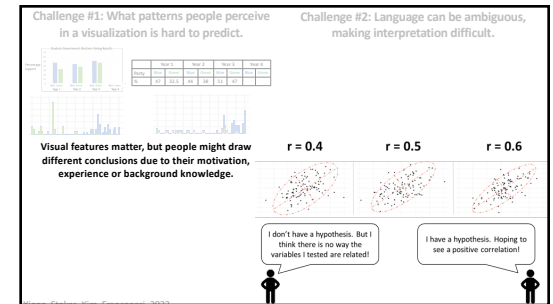
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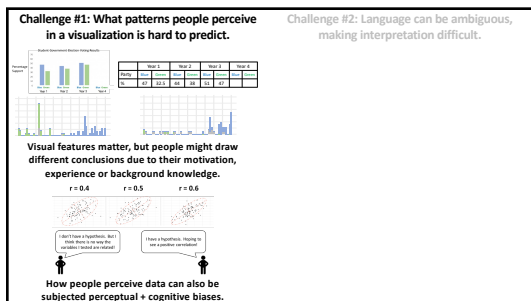
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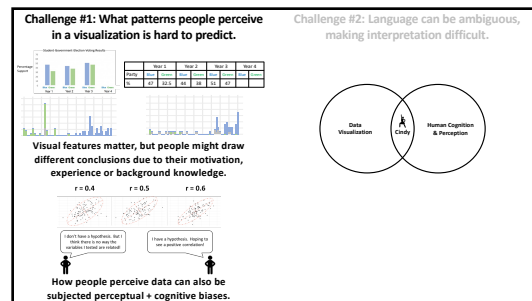
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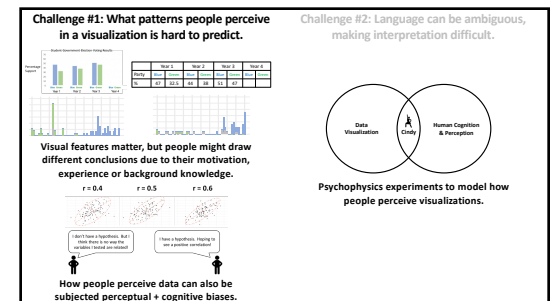
96



97



98



99

Challenge #1: What patterns people perceive in a visualization is hard to predict.

Visual features matter, but people might draw different conclusions due to their motivation, experience or background knowledge.

Challenge #2: Language can be ambiguous, making interpretation difficult.

Psychophysics experiments to model how people perceive visualizations.

How people perceive data can also be subjected perceptual + cognitive biases.

Xiong, Celis, Luikow, Franconeri, IEEE VIS 2019

100

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Cela, McColeman, Xiong, Franconeri, IEEE VIS 2020

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Kahneman, 2011

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New Safety GPS System Usage and Average # Accidents Involved

Xiong, Shapiro, Hullman, Franconeri 2020

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New Safety GPS System Usage and Average # Accidents Involved

Xiong, Shapiro, Hullman, Franconeri 2020

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Thinking about Causation

New Safety GPS System Usage and Average # Accidents Involved

Xiong, Shapiro, Hullman, Franconeri 2020

105

Thinking about Causation

New Safety GPS System Usage and Average # Accidents Involved

Xiong, Shapiro, Hullman, Franconeri 2020

106

Thinking about Causation

New Safety GPS System Usage and Average # Accidents Involved

Xiong, Shapiro, Hullman, Franconeri 2020

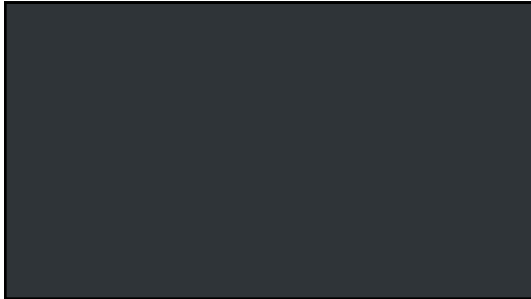
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Thinking about Correlation

New Safety GPS System Usage and Average # Accidents Involved

Xiong, Shapiro, Hullman, Franconeri 2020

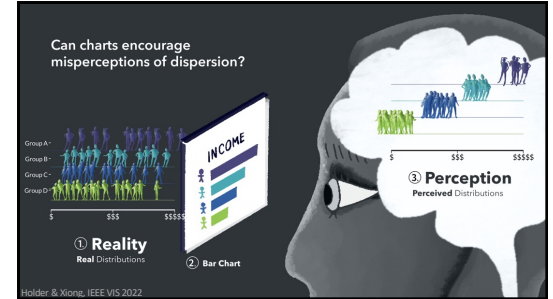
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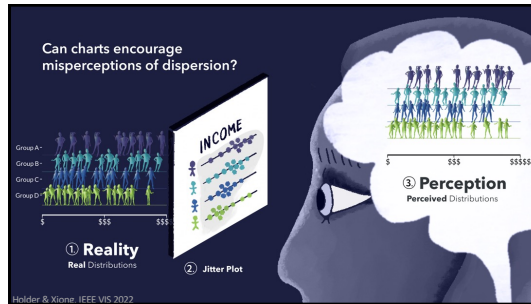
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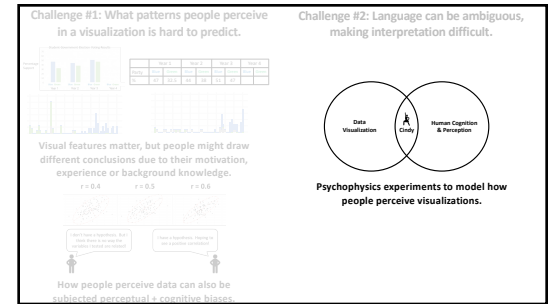
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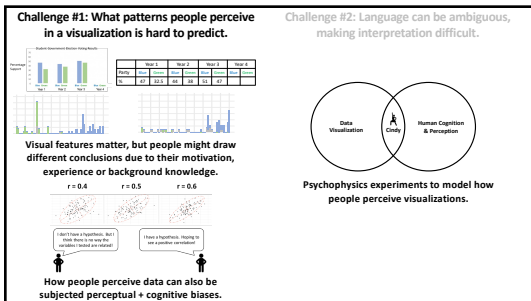
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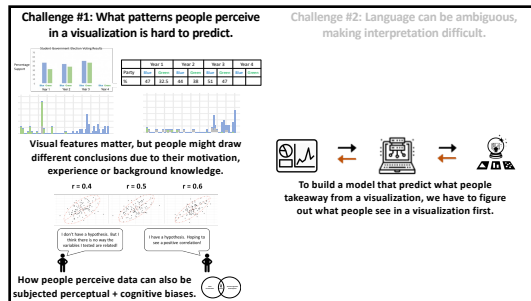
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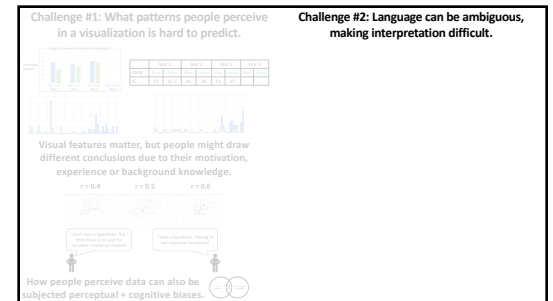
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121



122



123

Challenge #1: What patterns people perceive in a visualization is hard to predict.

Challenge #2: Language can be ambiguous, making interpretation difficult.

Visual features matter, but people might draw different conclusions due to their motivation, experience or background knowledge.

$r = 0.4$ $r = 0.5$ $r = 0.6$

How people perceive data can also be subjected perceptual + cognitive biases.

124

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125

Vertical

→

→ Comparison 1

Overlaid

→

→ Comparison 2

Adjacent

→

→ Comparison 3

Stacked

→

→ Comparison 4

126

Vertical

→

→ Comparison 1

Overlaid

→

→ Comparison 2

Adjacent

→

→ Comparison 3

Stacked

→

→ Comparison 4

127

Vertical

→

→ Comparison 1

Vehicle A Component 1	Vehicle B Component 1
Vehicle A Component 2	Vehicle B Component 2
Vehicle A Component 3	Vehicle B Component 3

What if we ask them to indicate which bars they compared?

128

Vertical

→

→ Comparison 1

Vehicle A Component 1	Vehicle B Component 1
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Vehicle A Component 3	Vehicle B Component 3

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129

Vertical

→

→ Comparison 1

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Vehicle A Component 2	Vehicle B Component 2
Vehicle A Component 3	Vehicle B Component 3

What if we ask them to indicate which bars they compared?

Most participants made multiple comparisons that contained the entire set

130

Vertical

→

→ Comparison 1

Vehicle A Component 1	Vehicle B Component 1
Vehicle A Component 2	Vehicle B Component 2
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What if we ask them to indicate which bars they compared?

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131

Vertical

→

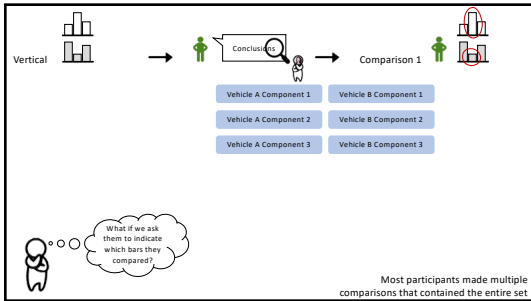
→ Comparison 1

Vehicle A Component 1	Vehicle B Component 1
Vehicle A Component 2	Vehicle B Component 2
Vehicle A Component 3	Vehicle B Component 3

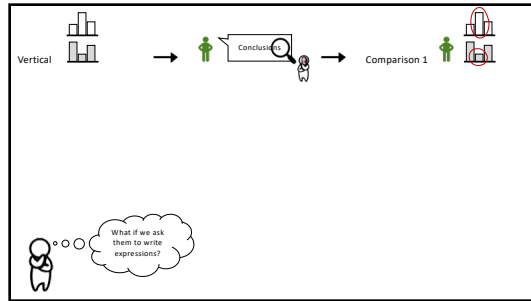
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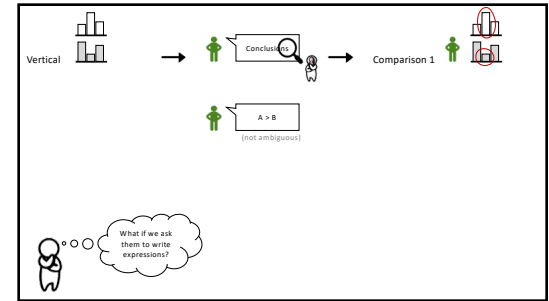
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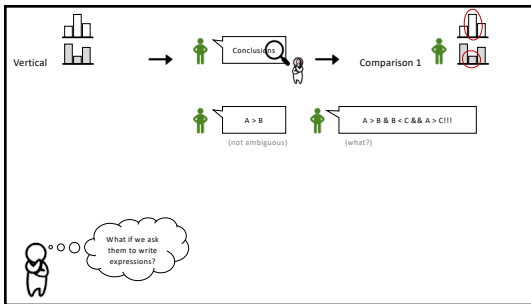
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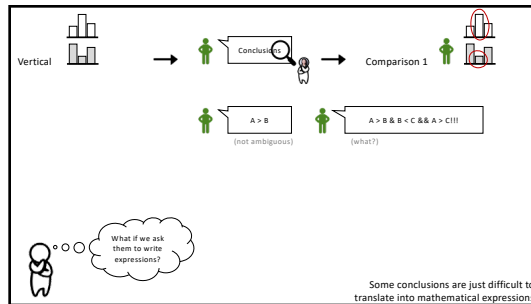
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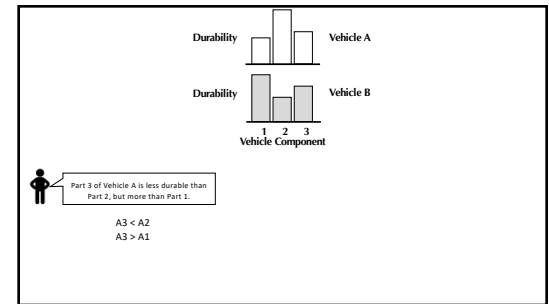
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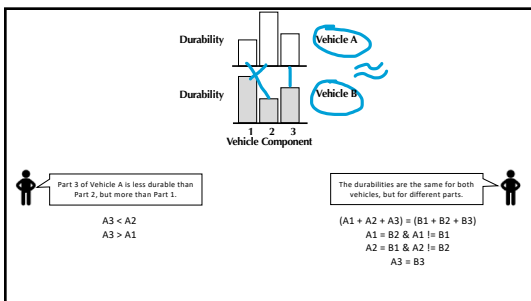
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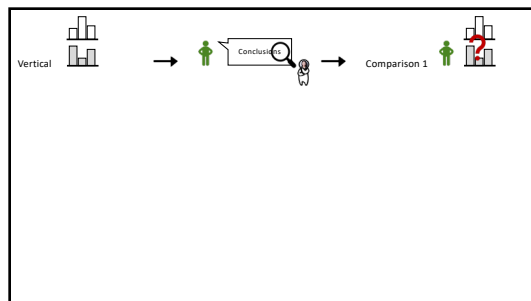
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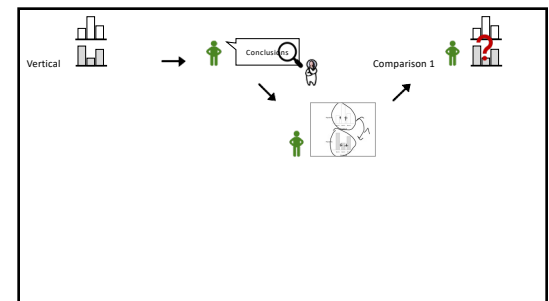
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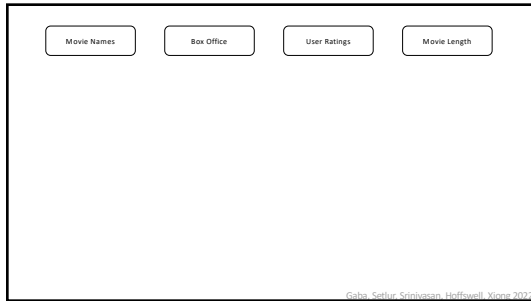
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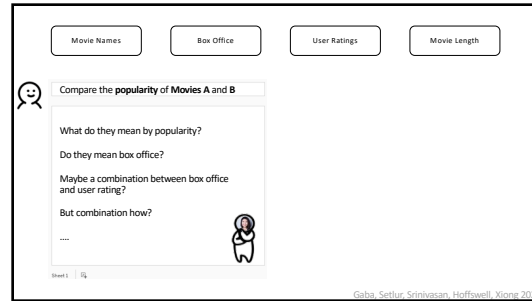
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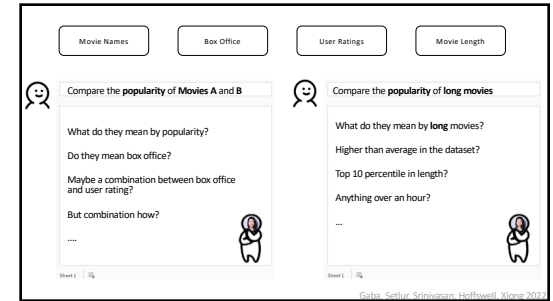
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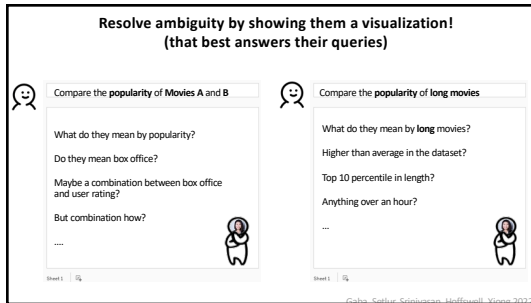
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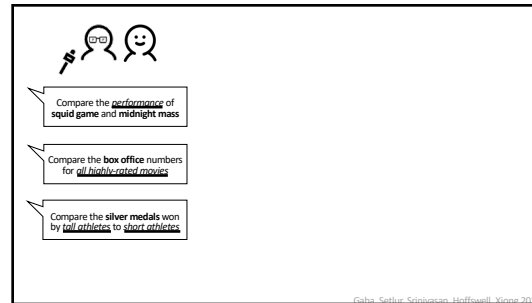
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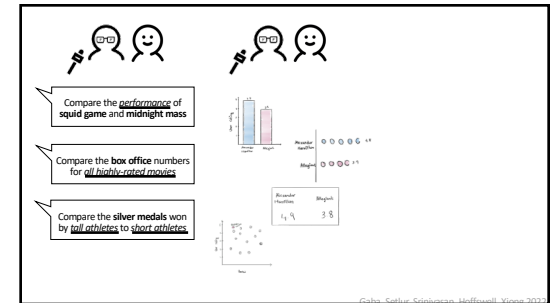
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163



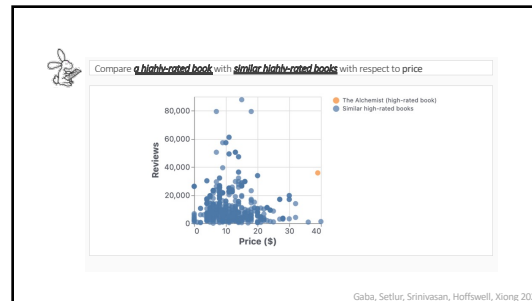
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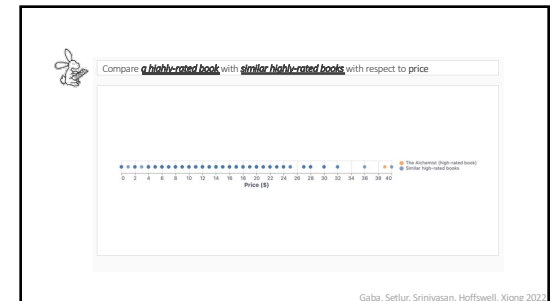
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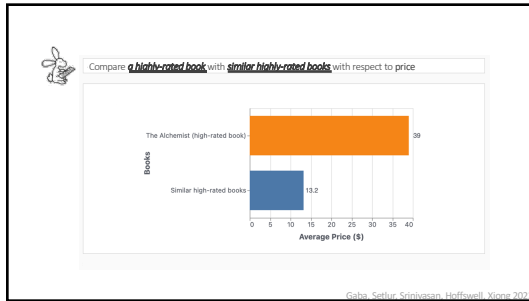
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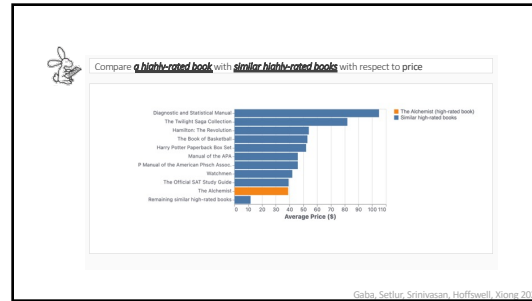
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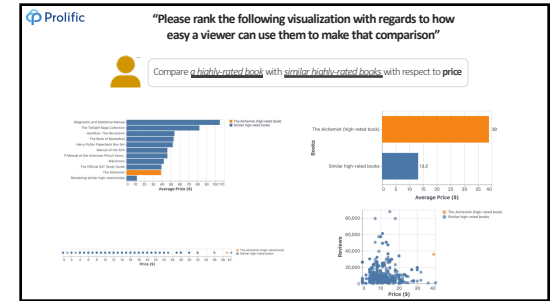
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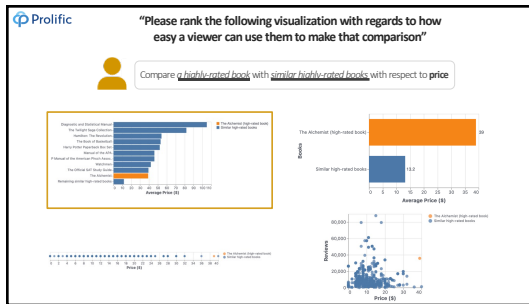
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170



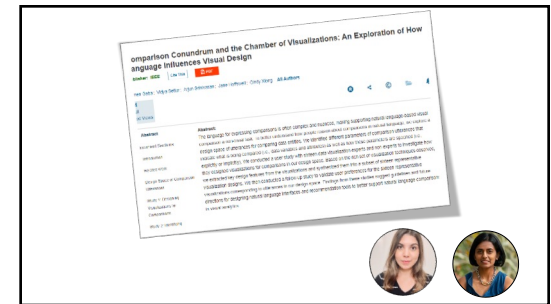
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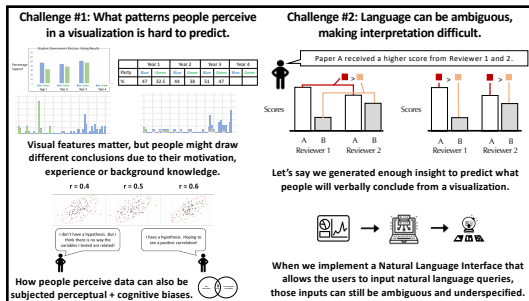
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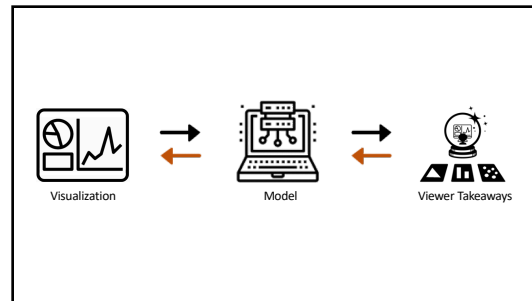
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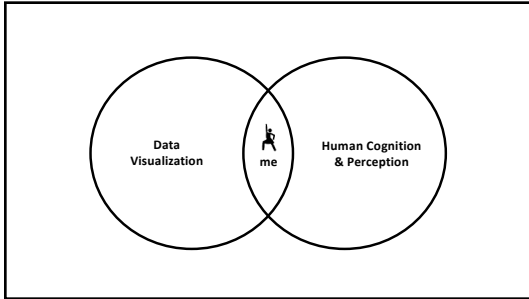
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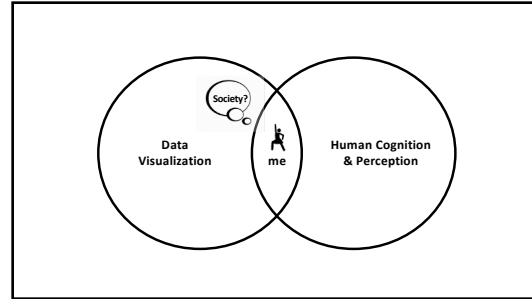
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179

A screenshot of the NIST website page titled "THE ORGANIZATION OF SCIENTIFIC AREA COMMITTEES FOR FORENSIC SCIENCE". The page lists various organizational details for the Human Factors Task Group, including governing documents, OSAC Registry, and a list of members.

180

A screenshot of the NIST website page for the Human Factors Task Group. A callout box is overlaid on the page with the text: "Identify opportunities for cognitive biases and provide input to writing practice standards and guidelines to help scientists and practitioners make better decisions".

181



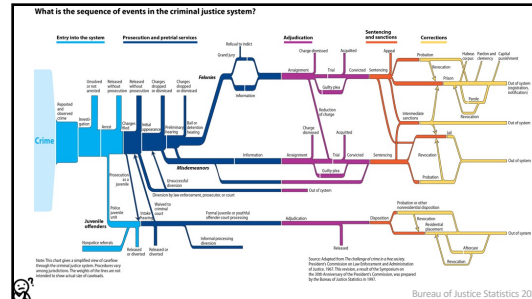
182

A slide titled "Trust and Data Visualization in Criminal Legal Reform". Below the title are four circular portraits of women, likely members of the task group.

183

The US criminal legal system is very complex.

184



185

A slide with three icons and text. The first icon is a bar chart with an upward arrow, with text "Growing demands for change.". The second icon is a building with a scale of justice, with text "District Attorney's (DA) offices and prosecutors play a major role.". The third icon is a magnifying glass over a document, with text "Progressive Prosecution through data transparency and dissemination.".

186

Online data dashboards.

↑

Progressive Prosecution through data transparency and dissemination.

187

Multnomah County District Attorney Bias Crime Cases

Dashboard Description

This dashboard shows case numbers from 2/17/18 to 7/30/22 for the Multnomah County District Attorney's Office (MCO) that resulted in final dispositions. The data is broken down by race/ethnicity, gender, and age. The dashboard also includes a map of the county and a list of cases.

Summary

Total Cases	Total Victims	Total Defendants	Most Common Bias
146	256	138	Race/Color

What is a bias crime?

Example

In 2018, four Latino men were charged as they left a gas bar. The group noticed a man yelling racial and homophobic slurs at them and tried to intervene. The man was arrested and charged with assault. The four men were charged with assault on a peace officer.

Definition

Generally speaking, a bias crime is one where the perpetrator commits a crime because of what they think that other person's identity is. Single's bias crimes are race/ethnicity, gender, sexual orientation, disability, national origin, and marital status.

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Lake County State's Attorney's Data Dashboard

Highlighted Data

See Data Trends on the navigation bar for more data.

Criminal Case Filings by Type

Felony APP Participant Race

189

commons VOLVO COUNTY, CA

Cases Referred to the Prosecutor

Total Cases February 2022: 340

Decisions after Case Review

190

Multnomah County District Attorney Bias Crime Cases

Highlighted Data

Criminal Case Filings by Type

Felony APP Participant Race

commons

191

Multnomah County District Attorney Bias Crime Cases

Highlighted Data

Criminal Case Filings by Type

Felony APP Participant Race

commons

How does sharing criminal legal data via dashboards impact public understanding + trust in the legal system?

192

Multnomah County District Attorney Bias Crime Cases

Highlighted Data

commons

Approval ratings for the DA

Understood the information

Reported trust in the data

How does sharing criminal legal data via dashboards impact public understanding + trust in the legal system?

193

Multnomah County District Attorney Bias Crime Cases

Highlighted Data

commons

Design of visualization dashboards seem to matter!

Approval ratings for the DA

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194

Multnomah County District Attorney Bias Crime Cases

Highlighted Data

commons

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*this is correlational data

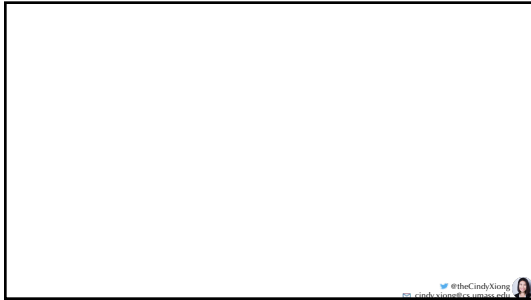
Approval ratings for the DA

Understood the information

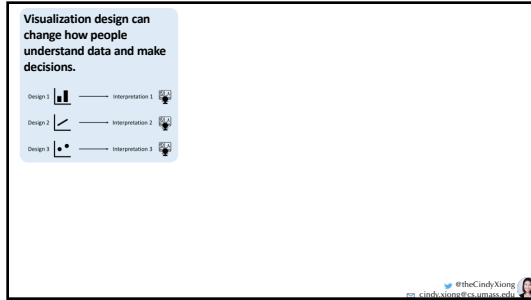
Reported trust in the data

How does sharing criminal legal data via dashboards impact public understanding + trust in the legal system?

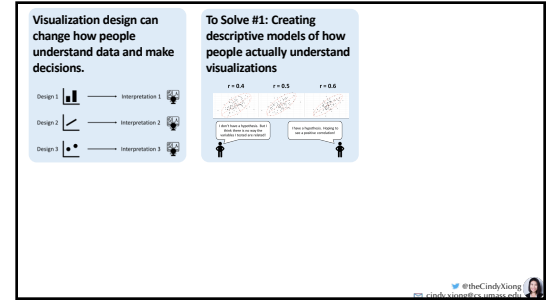
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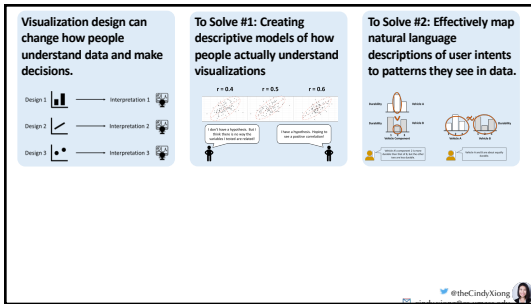
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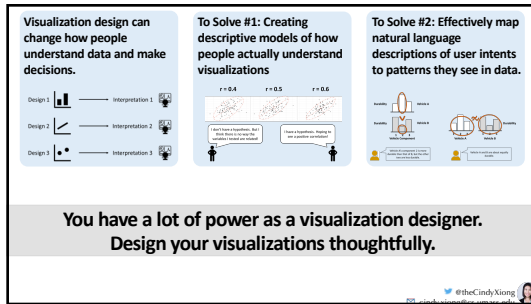
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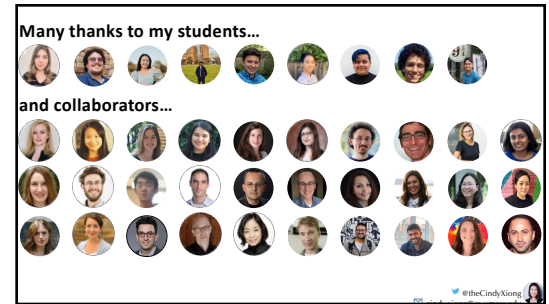
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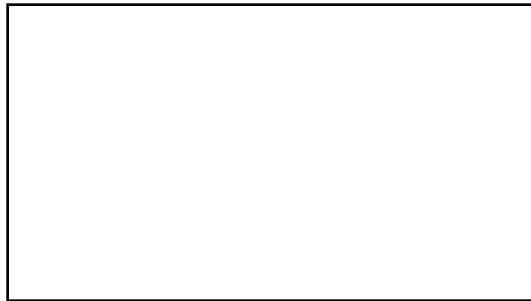
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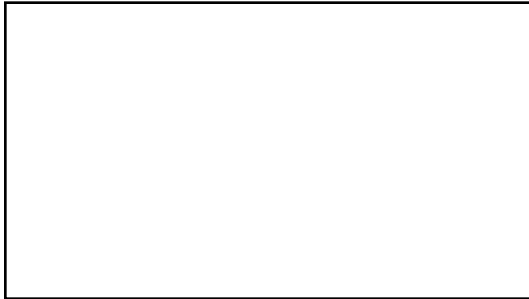
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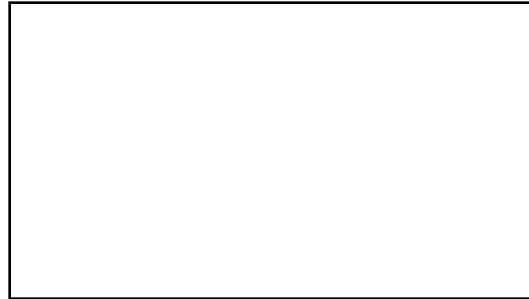
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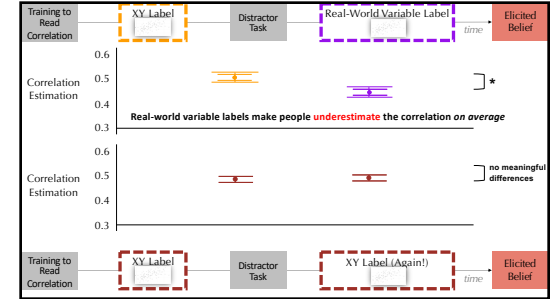
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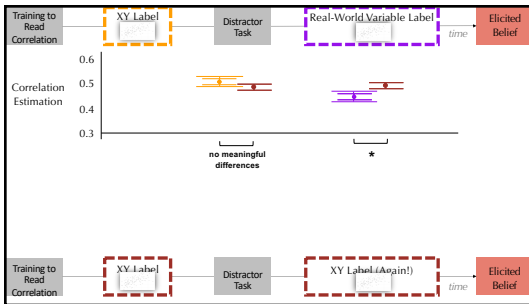
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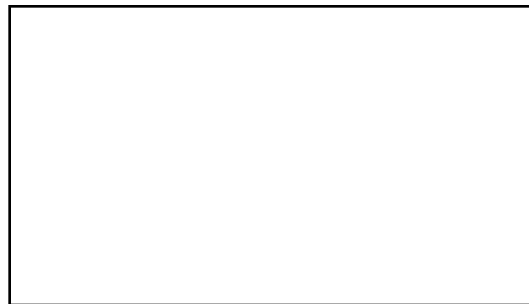
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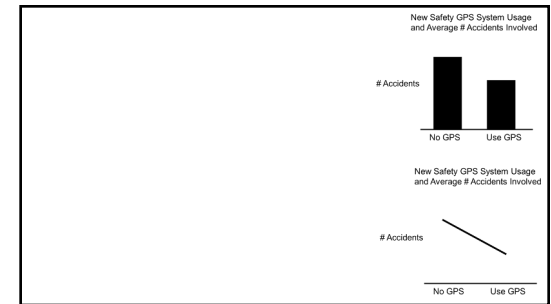
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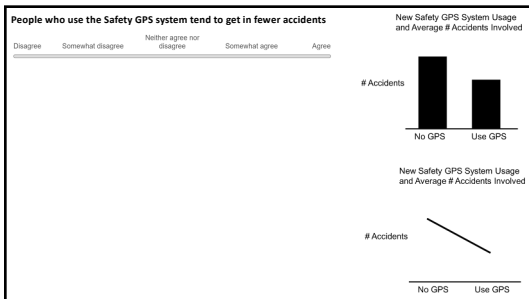
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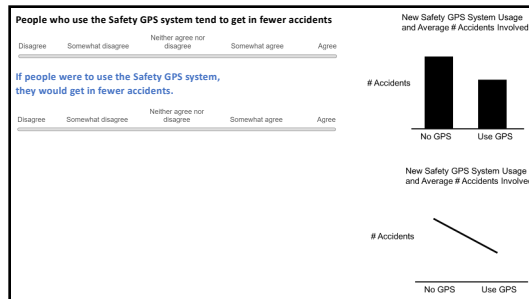
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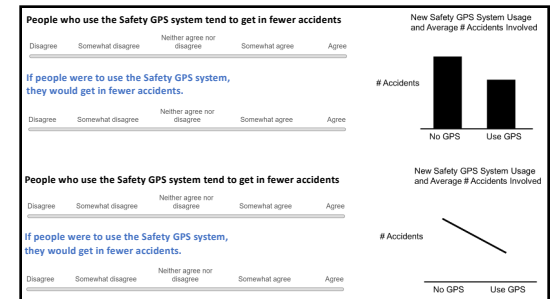
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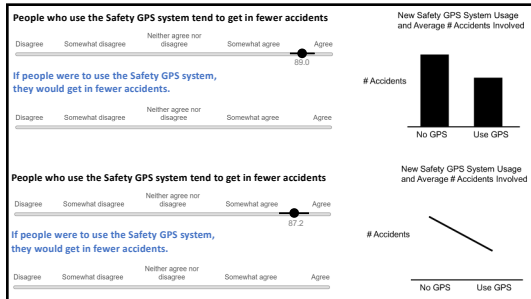
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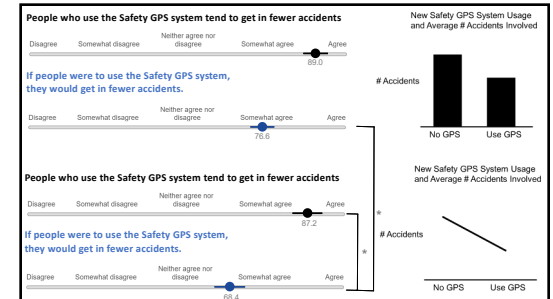
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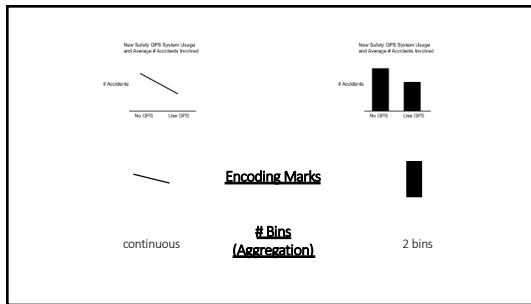
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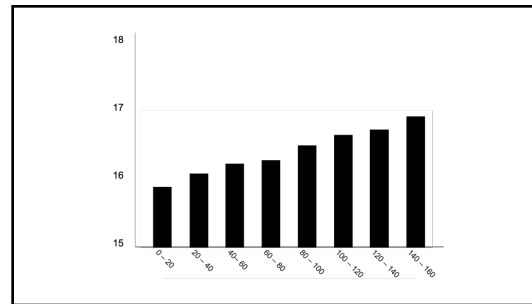
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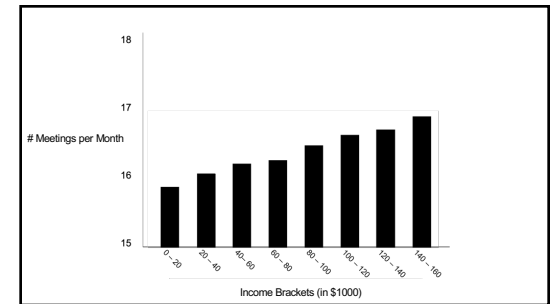
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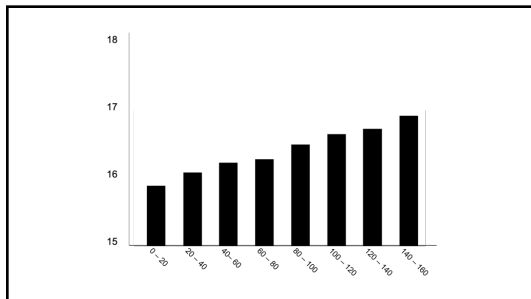
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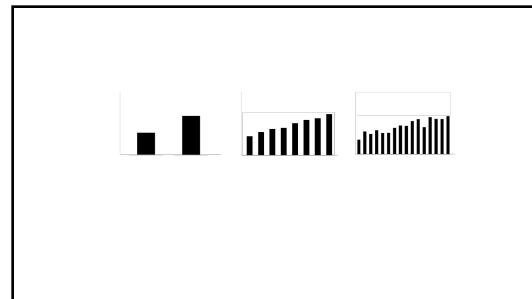
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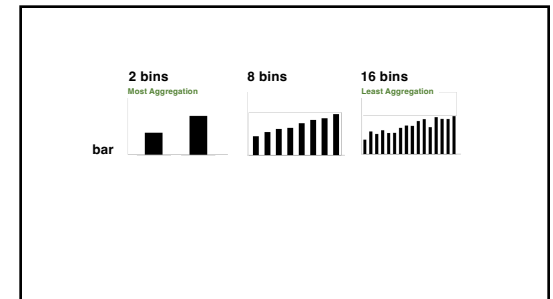
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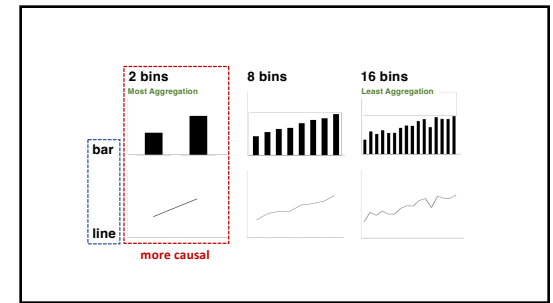
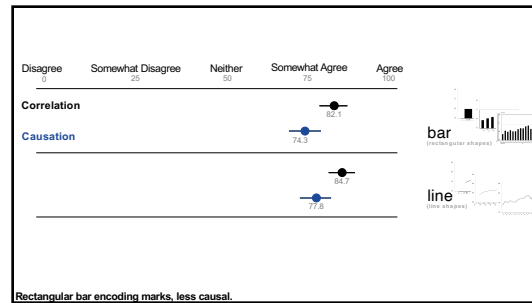
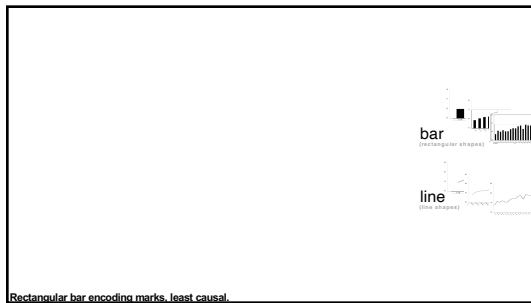
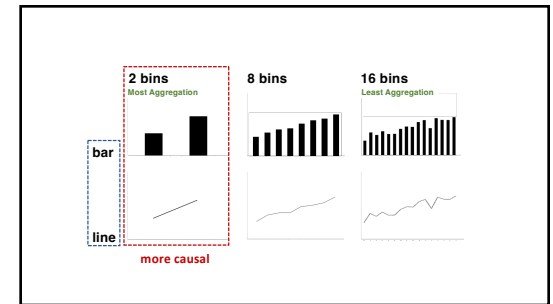
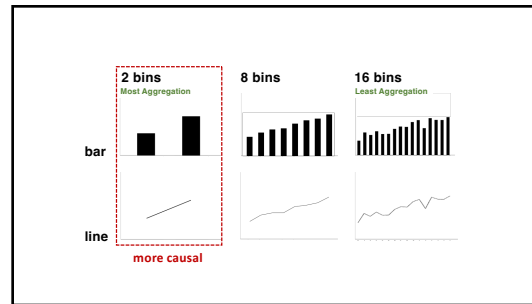
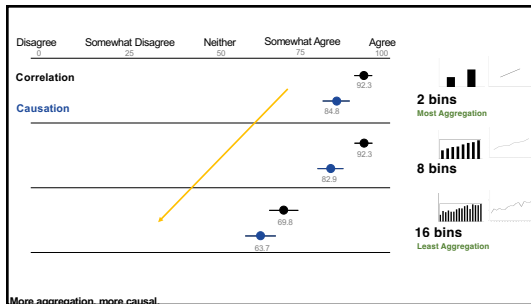
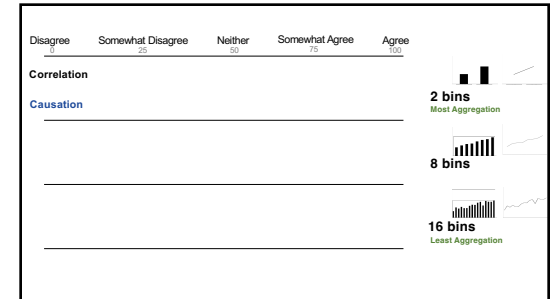
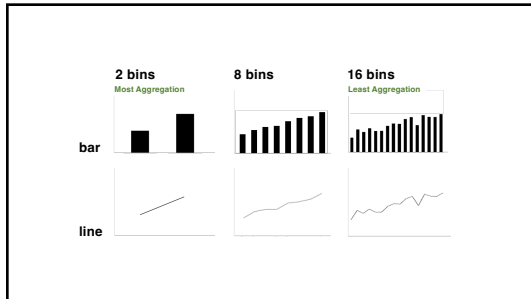
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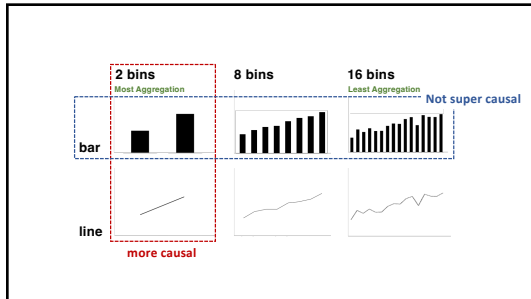


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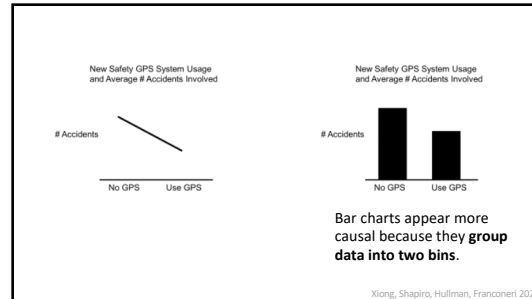


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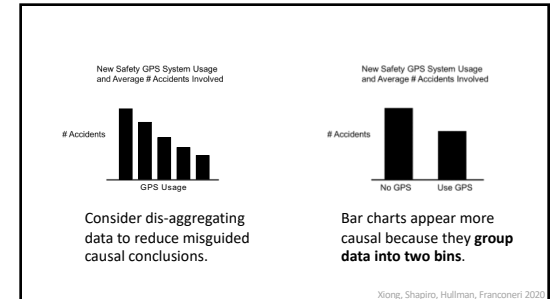




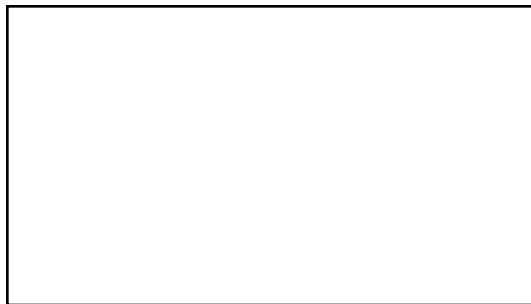
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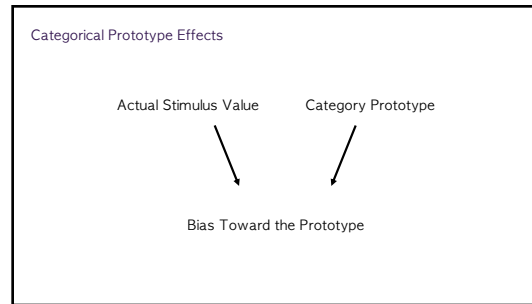
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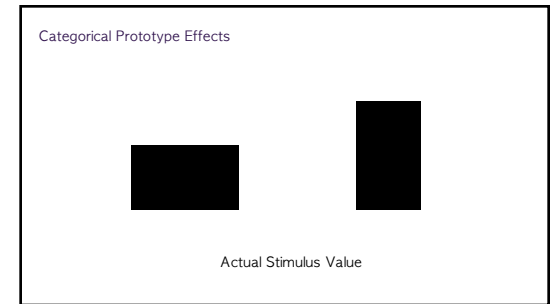
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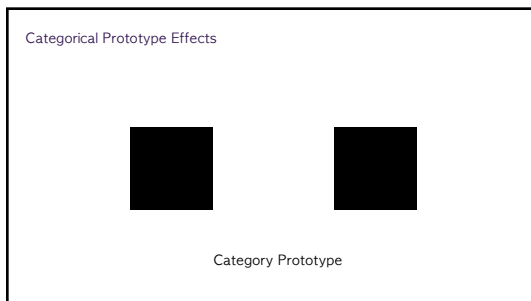
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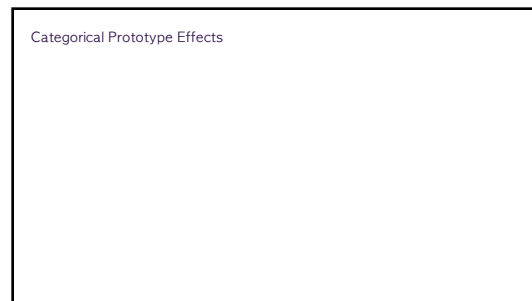
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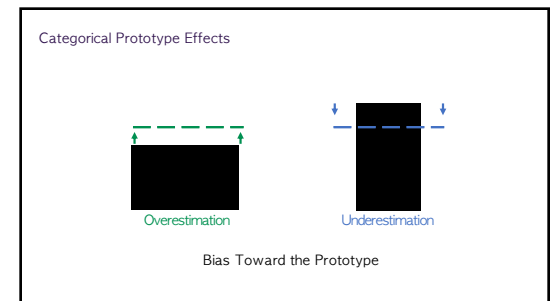
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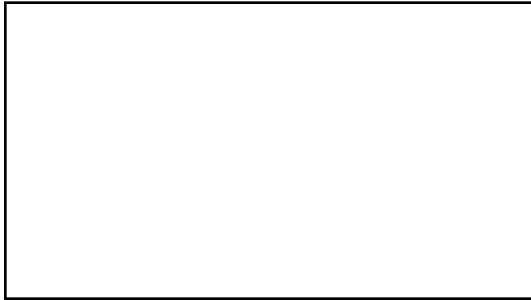
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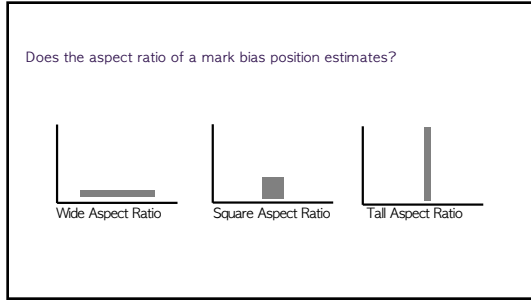
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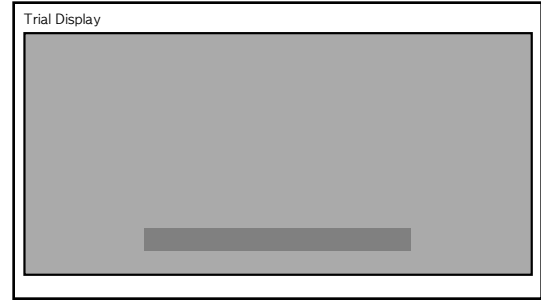
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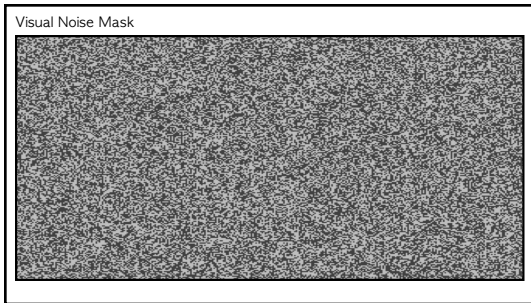
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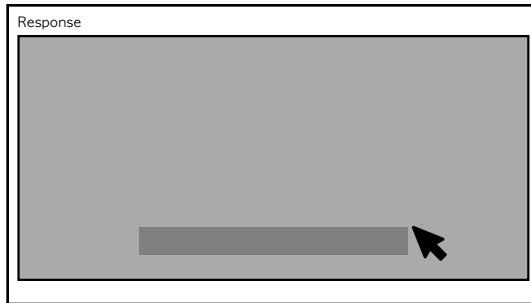
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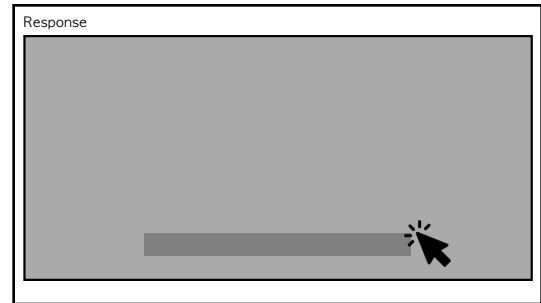
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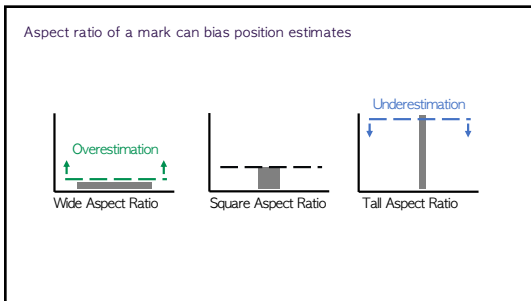
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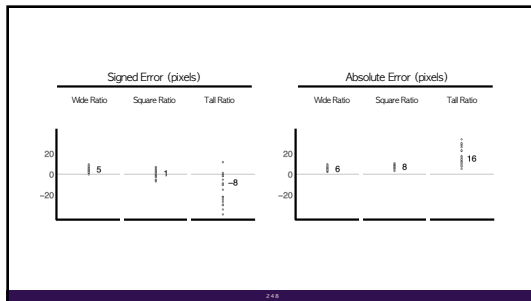
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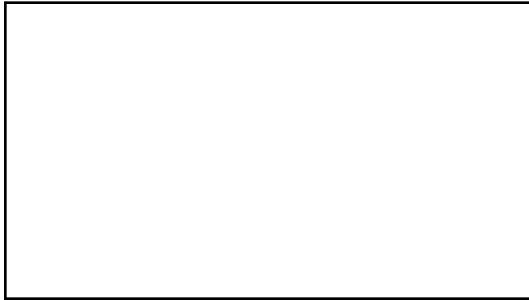
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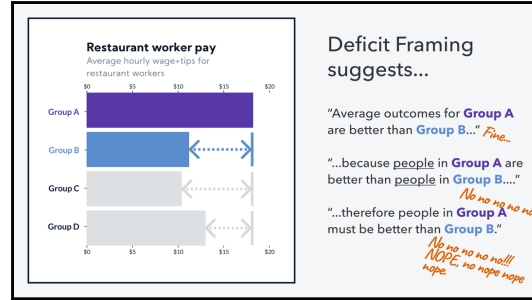
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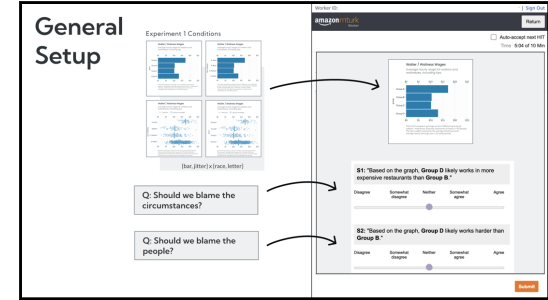
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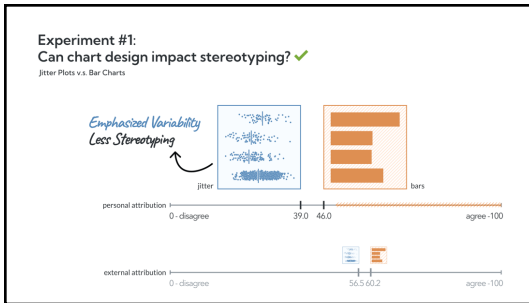
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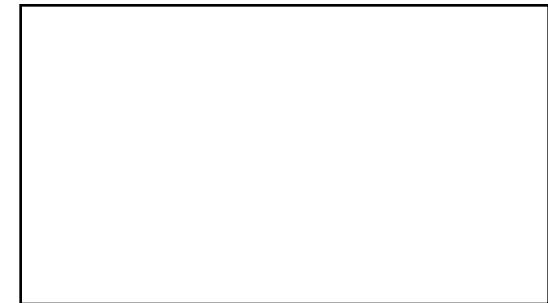
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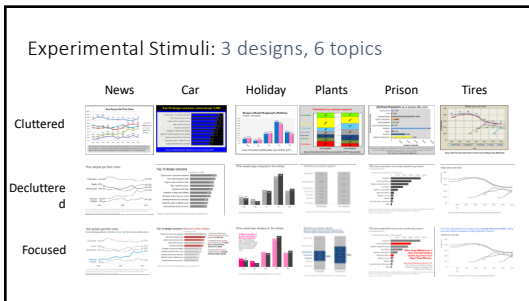
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	Winner	Verbal Description	Type
	adjacent	Component 2 is the most durable component in vehicle A.	Superlatives e.g. max = A
	adjacent	The total durability of components in vehicle A is higher than that in vehicle B	A-B comparison e.g., A > B
	overlaid stacked	Overall component 2s are more durable than components 3s.	1-2-3 comparison e.g., 1 < 3
	vertical	In vehicle B, component 1 is more durable than component 2.	Pair-comparison (AB) e.g., B1 > B2
	overlaid	Vehicle A's component 3 is less durable than vehicle B's component 3	Pair-comparison (1-2-3) 254

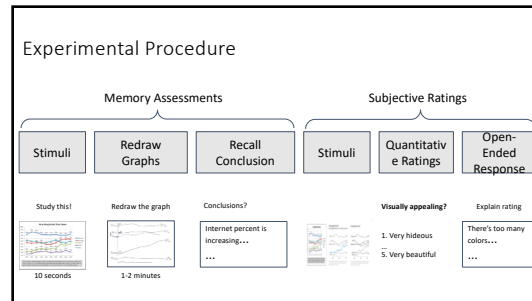
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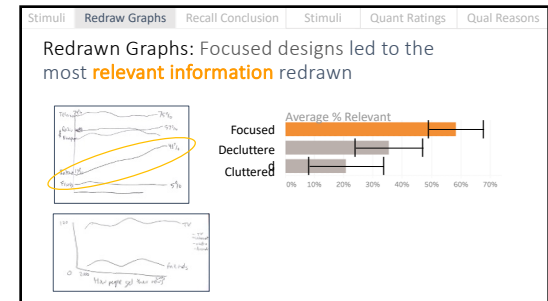
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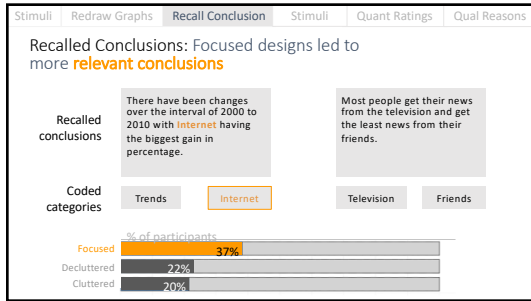
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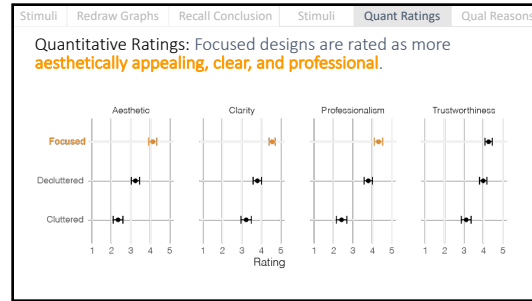
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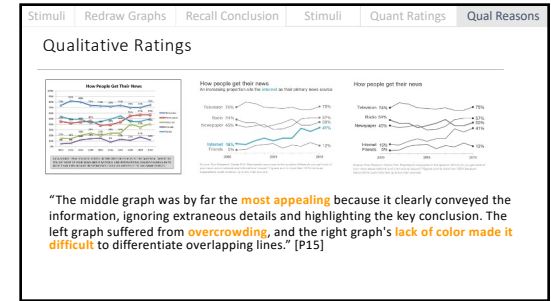
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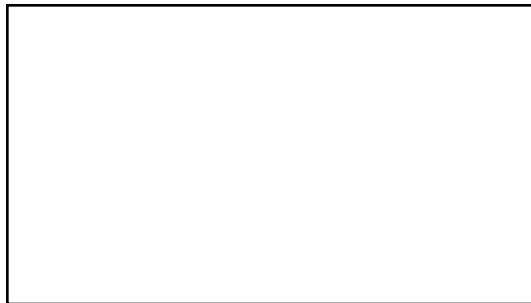
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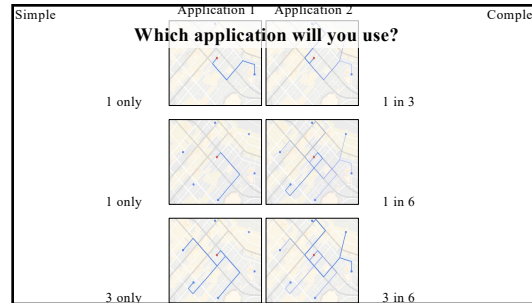
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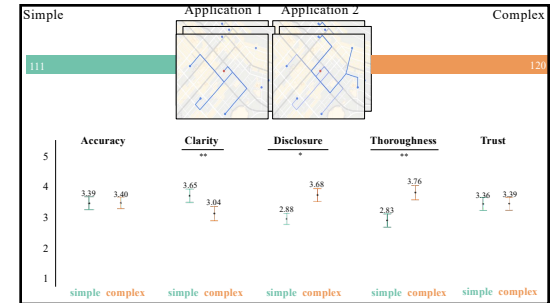
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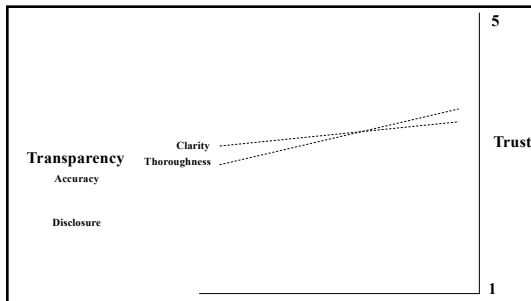
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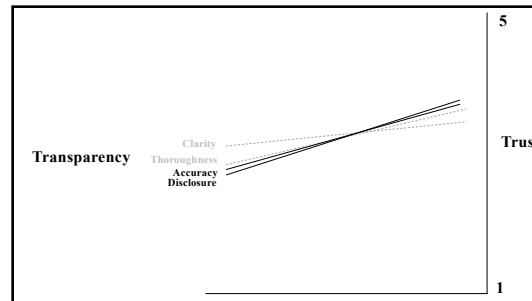
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