## Differentiating 'Human in the Loop' Decision Strategies

#### Sarah Walsh and Dr. Karen Feigh



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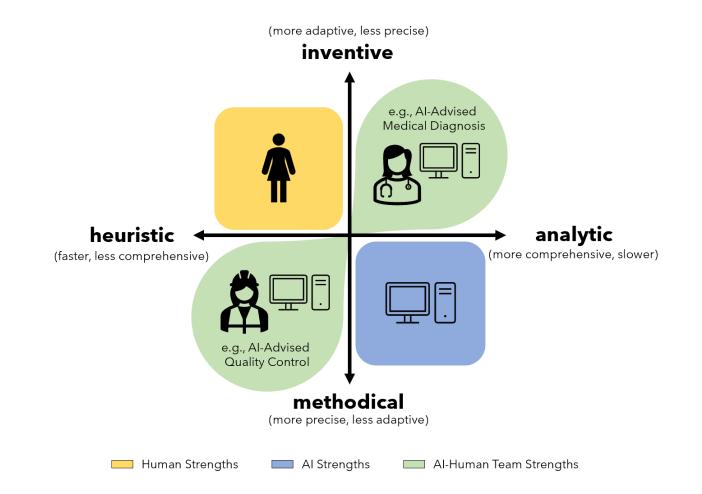
#### **Research Questions**

- Can we infer decision strategies from dynamic behavioral data?
- 2. Can we detect when people diverge in their decision making approach?
- 3. Can we classify these inferred decision strategies based solely on behavioral data?





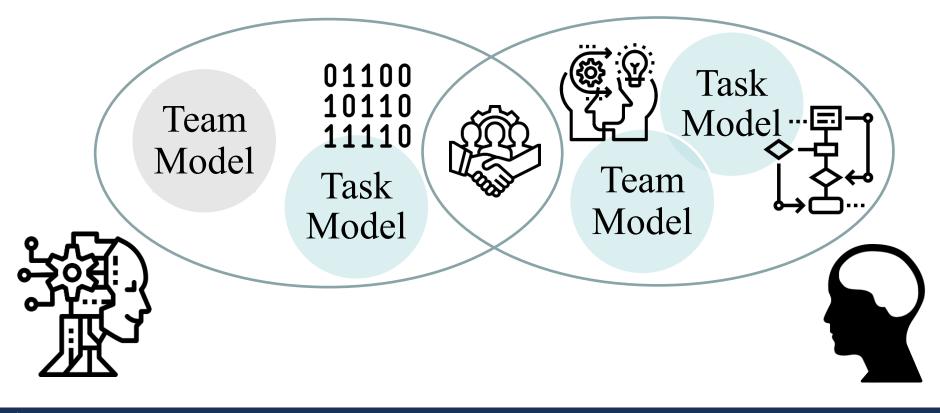
#### Human-Al Decision Making







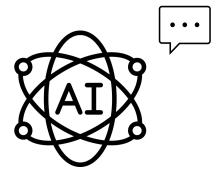
### Limitations in Human-AI Shared Mental Models



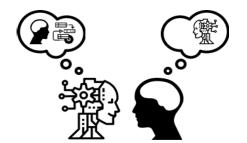
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#### Improving Human-Al Teaming:

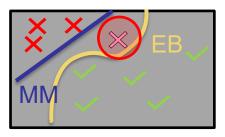


Explainable Al (Shin 2020, Preece 2021, Arya 2019)

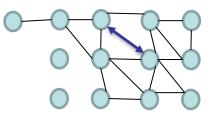


Al systems create Shared Mental Model with human teammates (Scheutz 2017)

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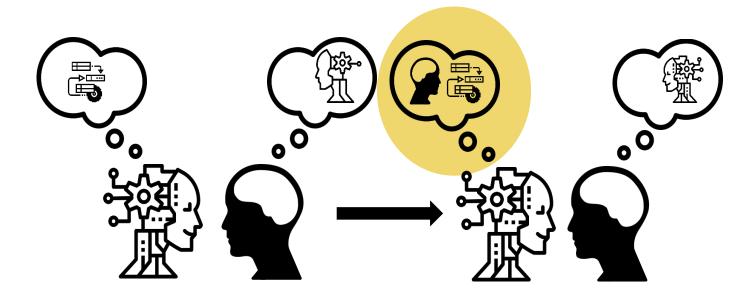
Improving human mental models of AI error boundaries (Bansal, 2020)



Bridging gaps between the AI and human's relative policies (Bastani, 2021)



#### **Create Shared Mental Model**



Al in human-Al teams often operate with little or no model of the human's cognitive state

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We need `learning human mental models' that are easy of an AI system to train and can support planning/decision-making (Chakraborti et al., 2017)

#### Approach to Learning Human Mental Models of Decision Making

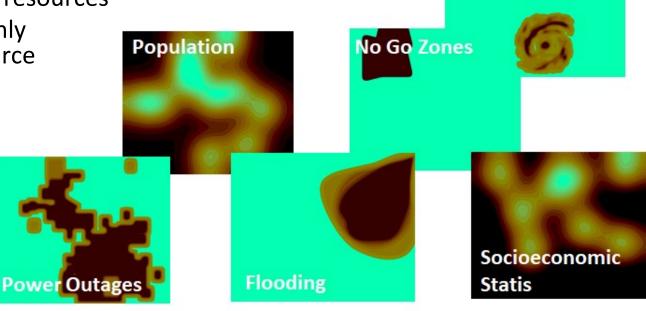
- **1**. Design an experiment to capture real-world decision making
- 2. Capture and classify decision strategies





#### Experiment with Geospatial, Sequential Task

- Participants will be assuming the role of a disaster relief planner making decisions about how to allocate resources prior to and during a storm
- The participants will have several heat maps that will aid in the decision making process overlaid on a US city
- The heat maps show gradients of better and worse locations to place resources
- Participants can only observe one resource at a time

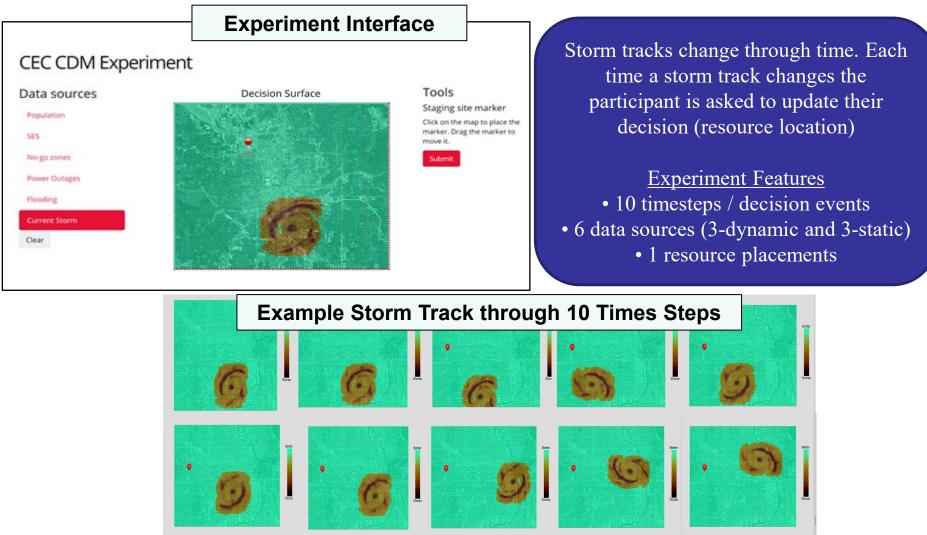






**Current Storm** 

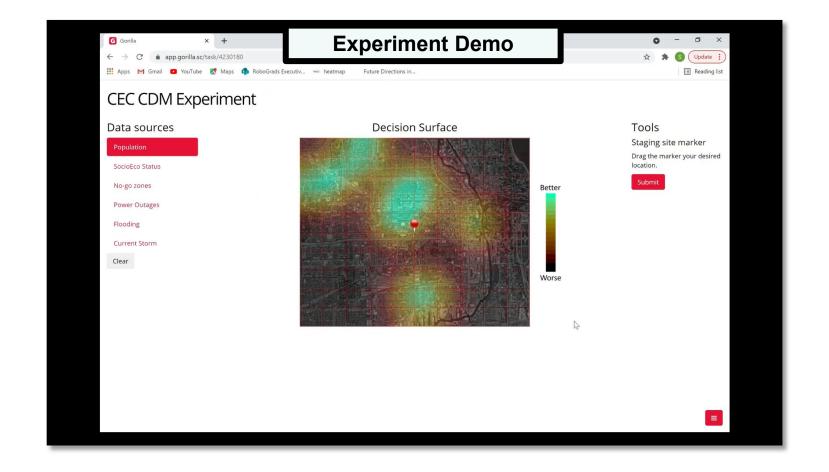
#### Experiment in a Sequential Environment







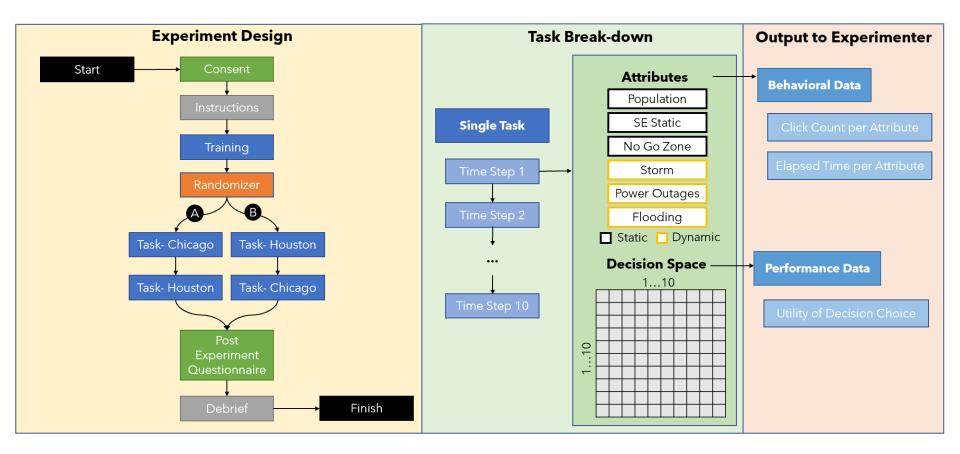
#### **User-Interface**







#### Administration of Experiment





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## Approach to Identifying DM Strategies

## Part 1: Label data using Partial Least Square Regression

Goal:

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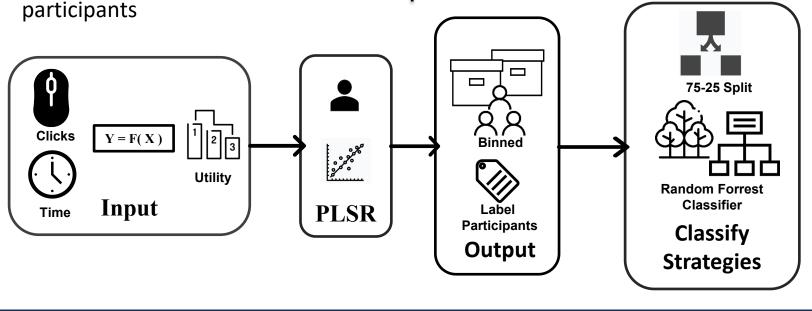
 Use behavior to classify decision strategies and predict decision strategies/mental models of participants

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Part 2: Reverse analysis to classify using Random Forrest

Goal:

- Classify DM strategy
- The output of the random forest is the class selected by most trees





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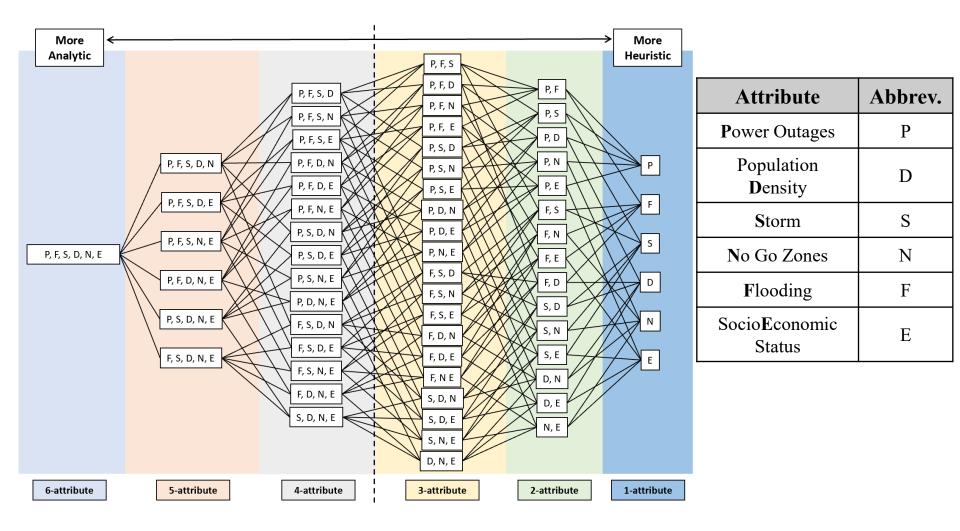
#### Results

- 1. Can we infer decision strategies from dynamic behavioral data?
- 2. Can we detect when people diverge in their decision making approach?
- 3. Can we classify these inferred decision strategies based solely on behavioral data?

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#### **Diagram of Possible Decision Strategies**



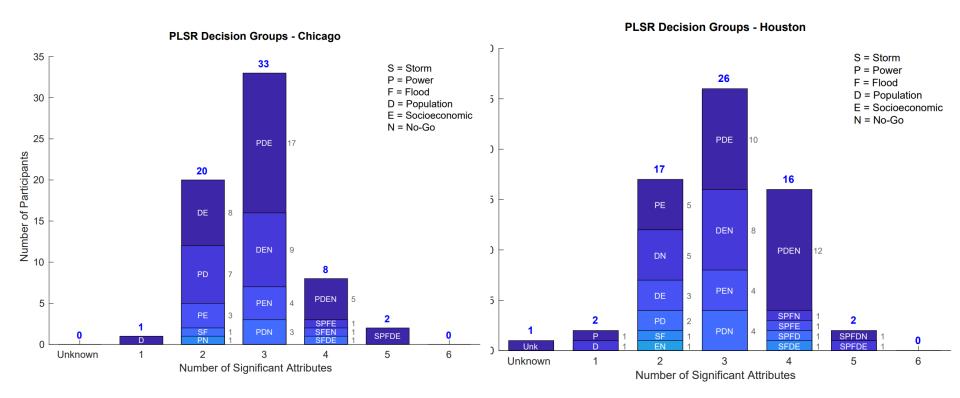


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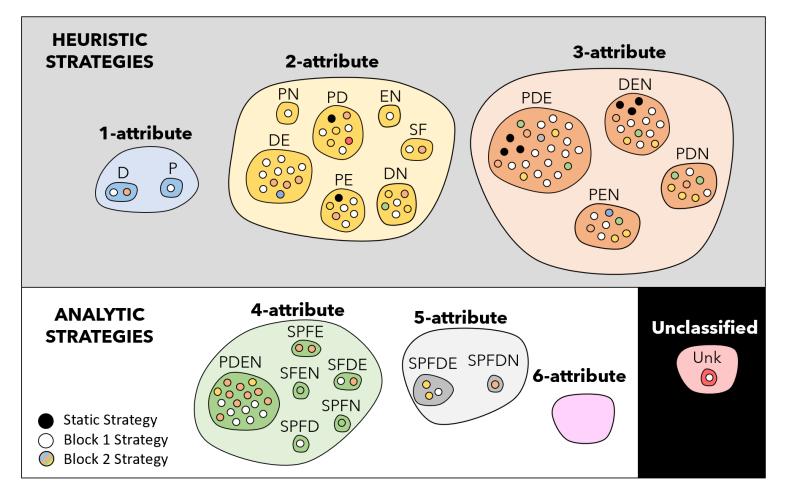
# Results: Can we infer decision strategies from dynamic behavioral data?







# Results: How stable are people's decision strategies?





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# Results: Can we classify individuals into these inferred decision strategies based solely on observable behavioral data?

| Chicago                     |          |           |             |
|-----------------------------|----------|-----------|-------------|
| Number of Trees:            |          |           | 700         |
| No. of splitting vars.:     |          |           | 10          |
| OOB estimate of error rate: |          |           | 7.8%        |
| Confusion Matrix:           |          |           |             |
|                             | Analytic | Heuristic | Class Error |
| Analytic                    | 373      | 27        | 6.7%        |
| Heuristic                   | 38       | 394       | 8.8%        |
| Houston                     |          |           |             |
| Number of Trees:            |          |           | 700         |
| No. of splitting vars.:     |          |           | 10          |
| OOB estimate of error rate: |          |           | 19.1%       |
| Confusion Matrix:           |          |           |             |
|                             | Analytic | Heuristic | Class Error |
| Analytic                    | 319      | 56        | 14.9%       |
| Heuristic                   | 85       | 273       | 24.3%       |

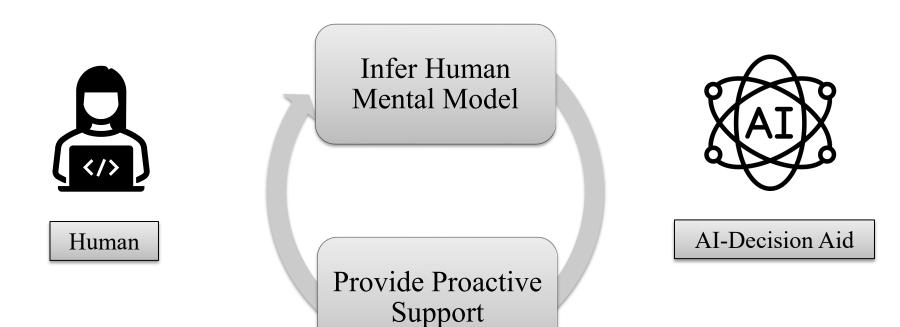


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#### Implications and Next Steps





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## Differentiating 'Human in the Loop' Decision Processes

#### Sarah Walsh and Dr. Karen Feigh

sewalsh@gatech.edu

karen.feigh@gatech.edu



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