Development of Mental Models in Decision Making Tasks

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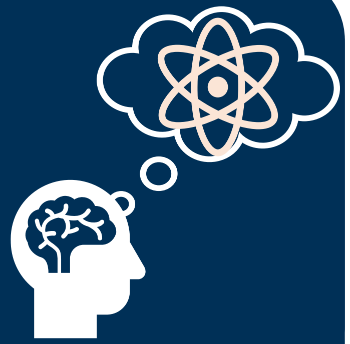
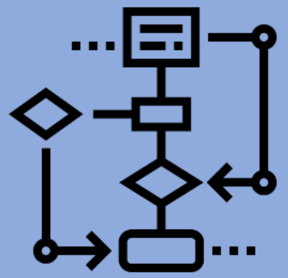
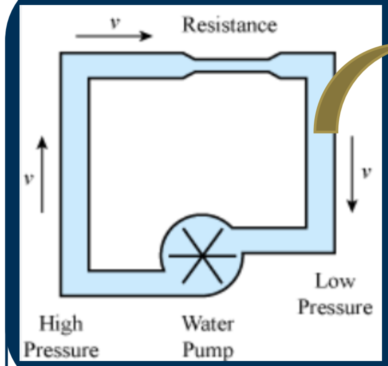
Definitions



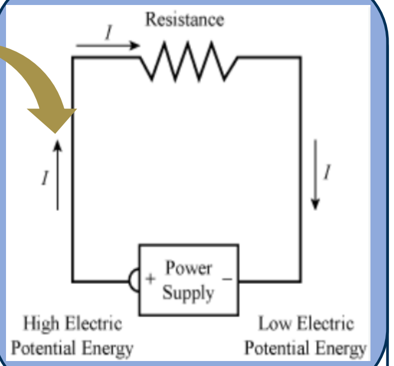
Humans **understand the world** by constructing working models of it in their mind



"Mental model (MM) is a **reasoning mechanism** that exists in a person's working memory" [1]



In unfamiliar domains, people tap into an existing MM and **import its relational structure**



Entities and **relations mapped** from model of the former to that of the latter

Provide gateways into one's perception of team and system & enable **identification of gaps and disparities** between agents in teams

[1] Johnson-Laird, P. N. (1983). Mental Models. Towards a Cognitive Science of Language, Inference and Consciousness. Cambridge, UK: Cambridge University Press.

Background

Elicitation is tough
1. Dynamic representations
2. Cannot be analyzed using one-off outcomes

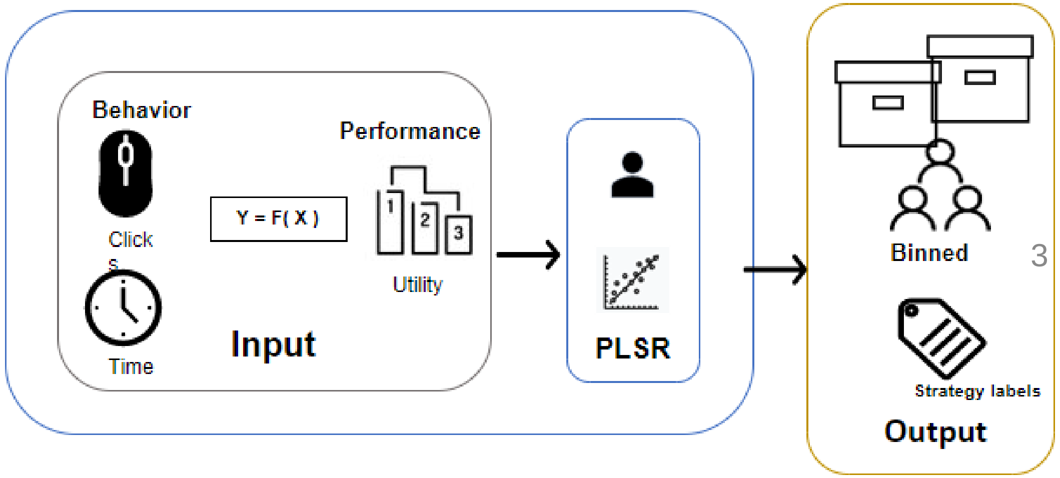
Elicitation methods are subjective, introspective or obtrusive

Certain elicitation methods could alter mental models

Objective elicitation methods are less validated

Partial Least Squares Regression

Combines the relative importance of each attribute to the decision & behavioral features that strongly correlate with used attributes



[2] Walsh, S. E., & Feigh, K. M. (2022). Understanding human decision processes: inferring decision strategies from behavioral data. Journal of cognitive engineering and decision making, 16(4), 301-325.

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Research Questions

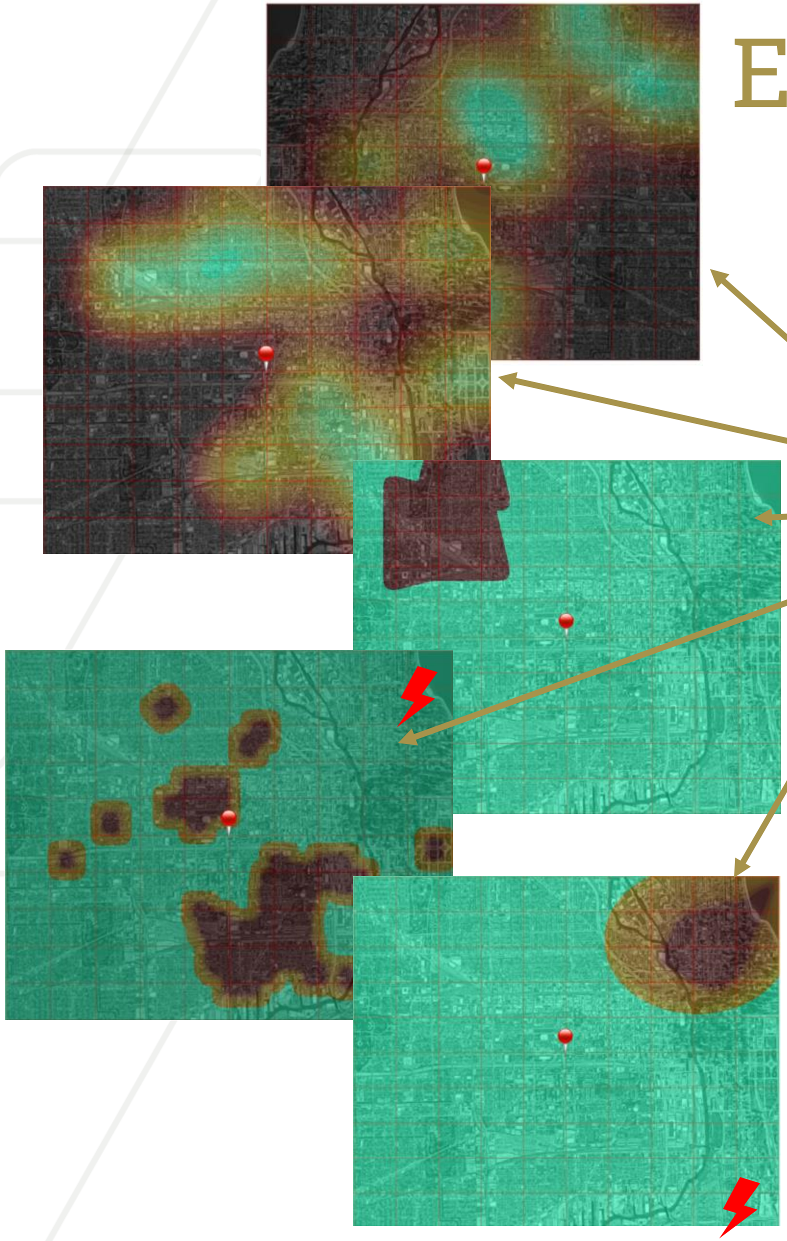
Test for Mental Model Elicitation

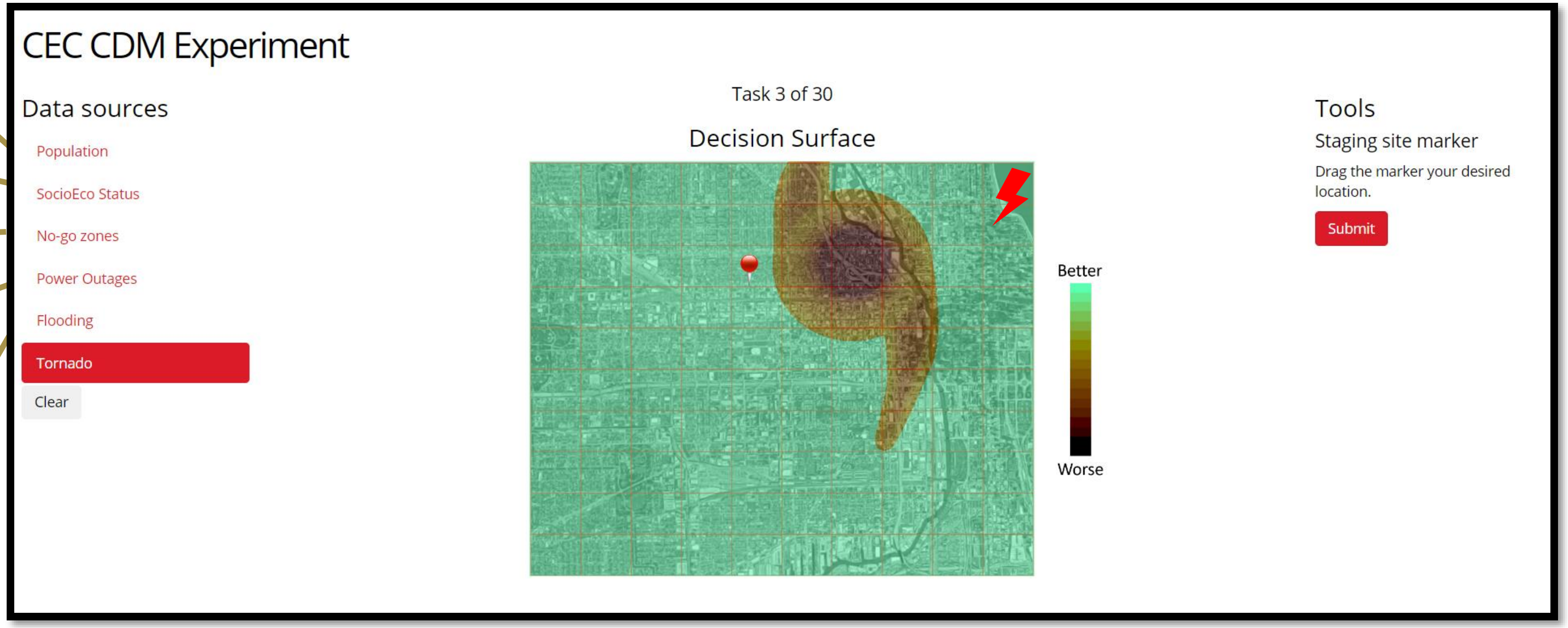
1. Can we observe the dynamic development of humans’ mental model of the task using process tracing in a complex geospatial environment?

Test for Stability and Predictability

2. Do mental model components stabilize with task progression? If yes, does this trend render predictability to human behavior as task familiarity increases?

Experimental Interface





Dynamic Attributes

- All data sources are **equally weighted**
- **Optimal spot** for resource is **unique**
- **Feedback** in the form of % score is provided

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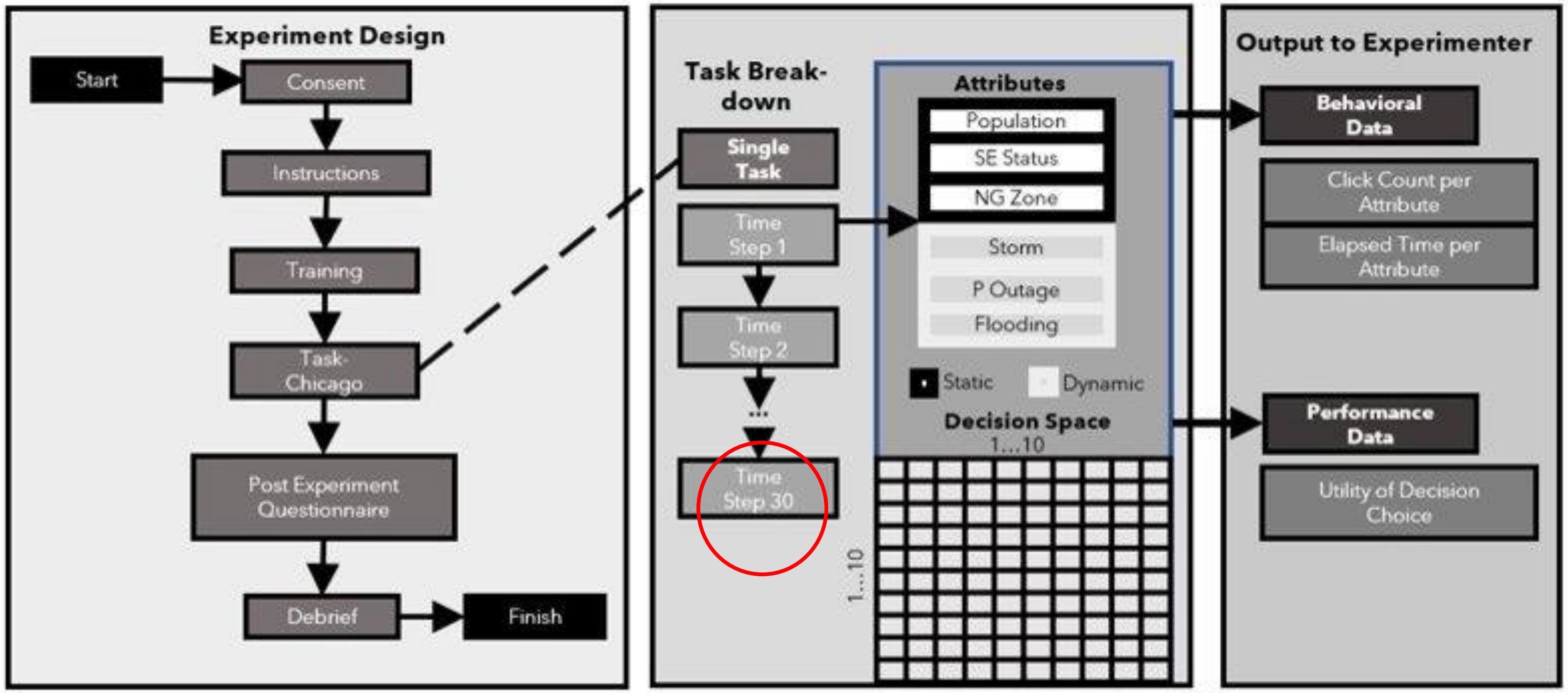
Experimental Flow



- Prior work [2] explored how participants' information access behavior could be classified into decision strategies across **10 time-steps**
- Decision strategies showed **trends of similarity** with time

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[2] Walsh, S. E., & Feigh, K. M. (2022). Understanding human decision processes: inferring decision strategies from behavioral data. Journal of cognitive engineering and decision making, 16(4), 301-325.

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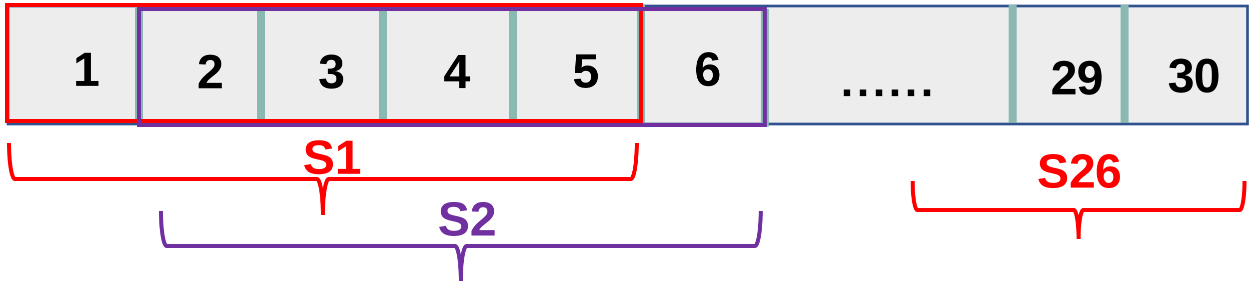
Metrics

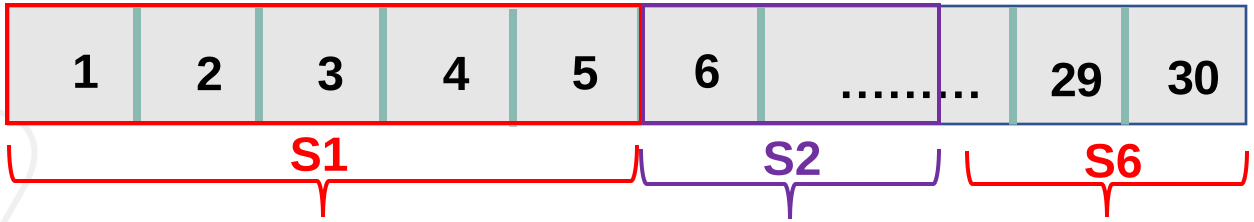
LD('PD', 'SD') = 1
LD('SPF', 'SDFN') = 2
…

- Performance → %UtChoice
- Similarity between strategies → Levenshtein Distances (LD)



LD(S1, S26)
LD(S2, S26)
.
.
.
LD(S25, S26)

Convergence (Stability)



LD(S1, S2)
LD(S2, S3)
.
.
.
LD(S5, S6)

Consistency (Predictability)

- Window size of 5 yielded optimal fit (R^2) and maximum number of classifications

Results

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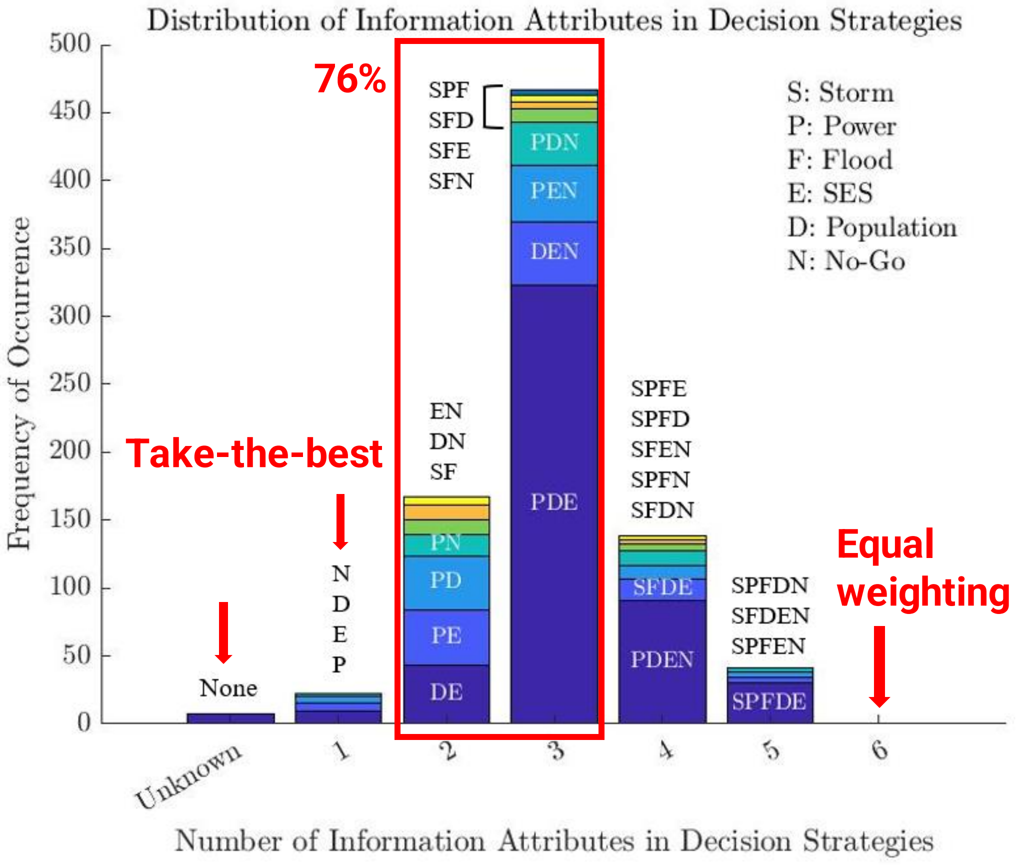
Mental Model Elicitation

- **Majority** participants used **3 attributes** followed by **2 attributes** to inform their decisions
- Only 3% of all strategies were '**Take-the-Best**'
- None with an **equal weighting** scheme
- There were 7 instances of participants acting arbitrarily i.e., having **no strategy**
- **P**ower, Population **D**ensity, and Socio-**E**conomic Status were most popular

Takeaway: Most users are imperfect decision makers, and they are neither completely heuristic nor analytic in their decision-making styles



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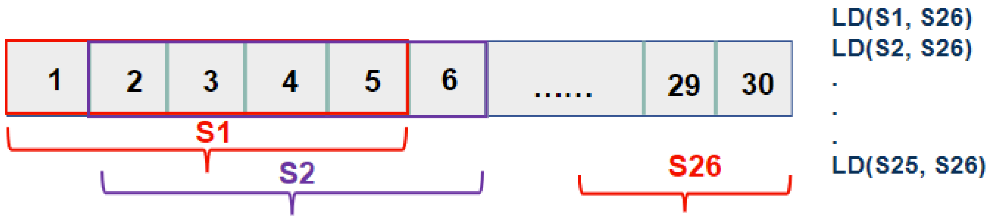
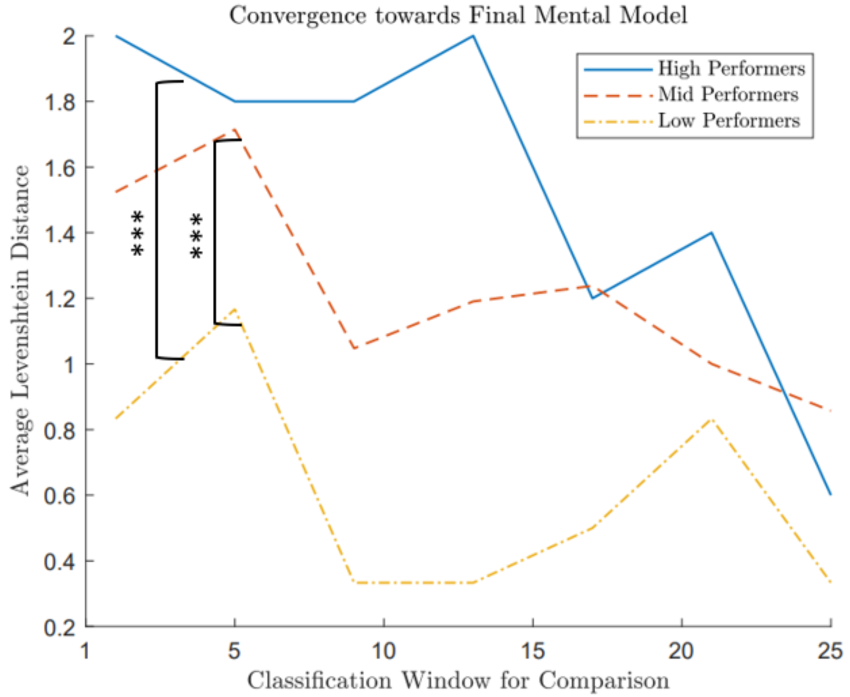
Performance and Strategy Stability

Performance distribution
High performers (*M = 87.3, SD = 6.8*)
Mid performers (*M = 76.2, SD = 8.2*)
Low performers (*M = 65.2, SD = 10.1*)

- Levenshtein Distances between each strategy with the **final strategy**
- **Convergence** towards final strategy is observed among all participant groups
- **Significant positive correlation** exists between change in strategy and performance among high performers
- **Weak correlation** among the lowest performers
- High performers **adapt then settle** → "reward seekers"
- Low performers **settle early** → "risk averse"

Takeaway: Stability of decision strategies is closely tied to task performance and competency





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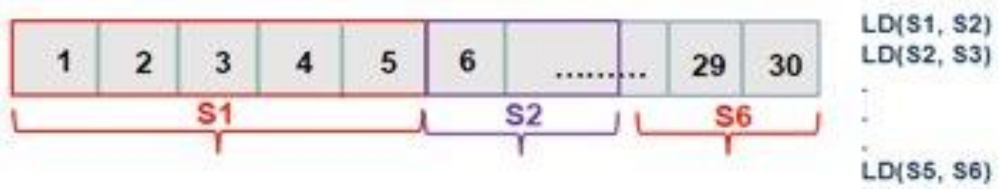
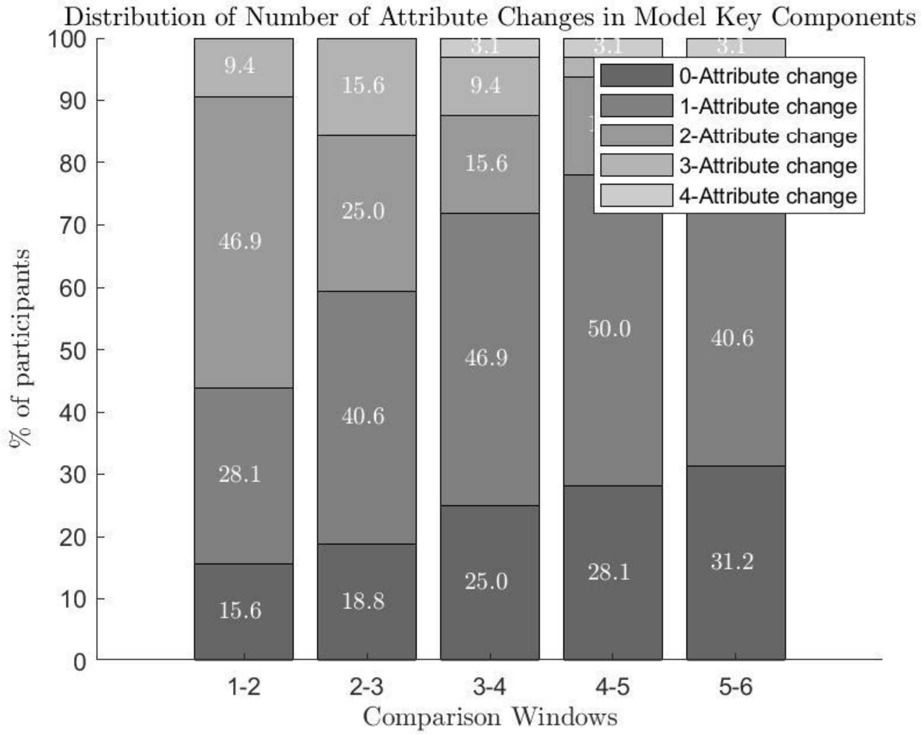
Predictability of Decision Strategies

- Predictability is quantified by observing **marginal changes** in strategies
- Levenshtein Distances between **consecutive classifications** of data points
- Proportion of participants with **LD = 0 and 1 goes up** monotonically over time
- **No** significant **correlation with performance** variation between consecutive timesteps
- **Lesser variations** in strategies regardless of performance improvement
- Decision strategies are **predictable** over time across all participant groups

Takeaway: With progression of tasks, decision strategies became more predictable





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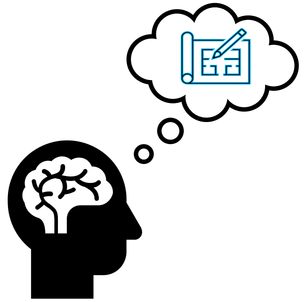
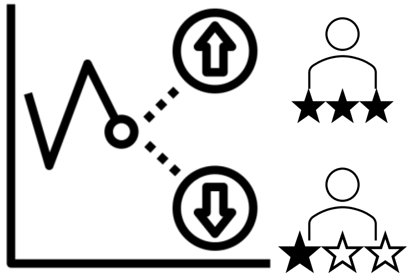
Conclusions

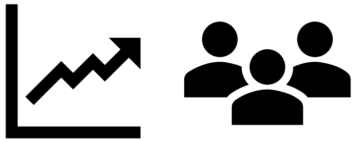
Heuristics and cognitive shortcuts are used throughout tasks



Stability (Convergence) of decision strategies varies with task competency



Predictability increases with task familiarity



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Acknowledgements

Slide deck

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Partial Least Squares Regression

Goal

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

Method

- Analyze our experiment with behavior (time spent, mouse clicks) as a function of decision choice for each resource (proxy for strategy) to find which resources were weighted the most by participants
- Participants are grouped with those that weighted resources similarly in order to classify and predict decisions

Formal Definition

The general underlying model of multivariate PLS is

$$X = TP^{\mathrm{T}} + E$$
$$Y = UQ^{\mathrm{T}} + F$$

where X is an $n \times m$ matrix of predictors, Y is an $n \times p$ matrix of responses; T and U are $n \times l$ matrices that are, respectively, projections of X (the X *score*, *component* or *factor* matrix) and projections of Y (the Y *scores*); P and Q are, respectively, $m \times l$ and $p \times l$ orthogonal *loading* matrices; and matrices E and F are the error terms, assumed to be independent and identically distributed random normal variables. The decompositions of X and Y are made so as to maximise the covariance between T and U.

Source: Wikipedia

Partial Least Squares Regression: Setup

Behavior is a function of your decision strategy (proxy of decision strategy is decision choice)

Behavior

- % Time on Power
- % Time on Flood
- % Time on Storm
- % Time on Population
- % Time on No-Go Zones
- % Time on SES
- Total Time
- # Clicks on Power
- # Clicks on Flood
- # Clicks on Storm
- # Clicks on Population
- # Clicks on No-Go Zones
- # Clicks on SES
- Total Clicks

Y = F (X)

Decision Choice

- Utility on Power Map
- Utility on Flood Map
- Utility on Storm Map
- Utility on Population Map
- Utility on No-Go Zones Map
- Utility on SES Map

PLSR Output

- Coefficients of each participant indicating which resources are most likely to correspond to their observed behavioral data

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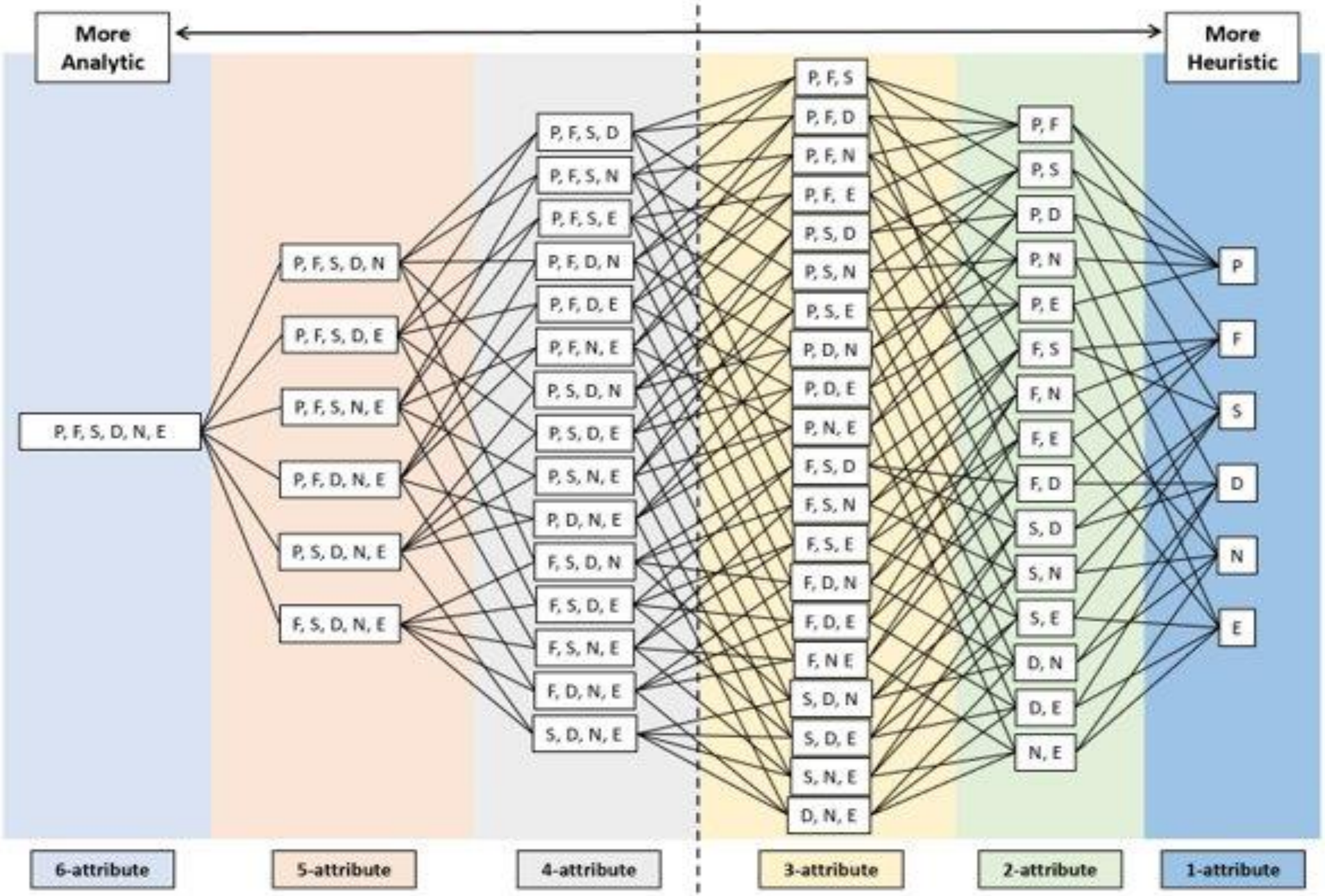
Combinations of Decision Strategies



Information Attribute	Abbr.
Power	P
Flooding	F
Current **S**torm	S
Population **D**ensity	D
No-Go Zones	N
Socio-**E**conomic Status	E

Scoring Policy

Decision Choice

- Utility on Power Map
- Utility on Flood Map
- Utility on Storm Map
- Utility on Population Map
- Utility on No-Go Zones Map
- Utility on SES Map

→

Equal Weighting

Linear Superposition Of Utilities

→

Final Score

Min-Max Normalization

→

Feedback to participant after each submission