Individual Differences in Human Clustering

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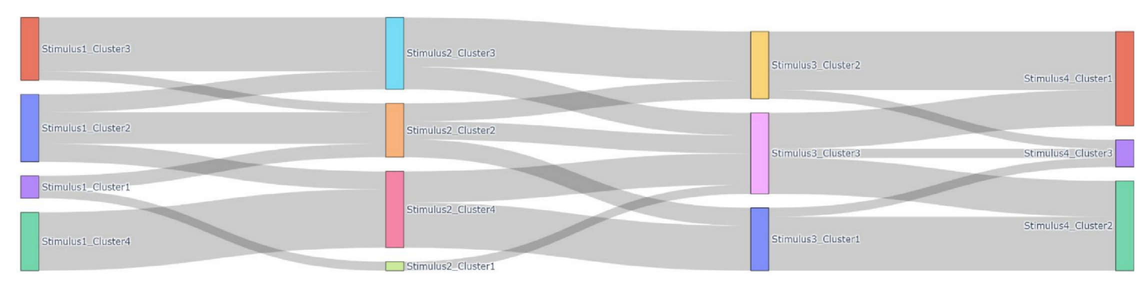
INTRODUCTION

- Human visual clustering: the process of dividing a set of points into "similar" groups.
- Despite knowledge of general principles from the Gestalt tradition, the reasons for individual variability in clustering remain unsolved. We suspect traits such as personality, statistics anxiety, and perception may play a role.
- Some models of human clustering have suggested that clustering might underlie numerosity estimation (Im et al., 2016; van Oeffelen & Vos, 1982) and that this link is not associated with visual crowding, a perceptual phenomena (Chakravarthi & Bertamini, 2020).
- However, one major limitation of prior work is that they did not collect the precise clusterings that participants perceived, rather, they only asked participants to report the number of clusters.
- In this study, we investigate the association between visual clustering and numerical cognition more closely by comparing participants clusterings with their magnitude comparisons and magnitude estimations involving the same exact stimuli.

METHODS

- N = 40 participants; each clustered 28 stimuli (4 stimuli for 10 points, 15 points...40 points)
- magnitude comparisons of stimuli with numerosity ratios between X and X, including comparisons between all pairs of cluster structures.
- Additionally, participants estimated the numerosity of every stimulus.

Stimuli



Sankey Diagrams for 20 points

RESULTS

- **Competitive clustering**: an iterative parallel model which combines hebbian learning process with lateral inhibition and uses operations which are biologically plausible. For each stimulus, the model is randomly initialized with multiple active neurons. Each neuron responds to a location on the stimulus where a cluster centroid might be. The activations of these neurons are then manipulated using two processes.

1. *Hebbian learning*: For each point in the stimulus, the closest 10 neurons receive an activation boost, while the others are reduced. The location of the neurons are changed to move closer to the point.
2. *Lateral inhibition*: For each neuron, the closest 10 neurons receive a reduction in activation.

– Both processes result in the activations of most neurons converging to zero and some neurons to stabilizing at specific regions of the stimulus. These neurons, which are above an activation threshold, are then used as cluster centroids to determine the cluster membership of the points.

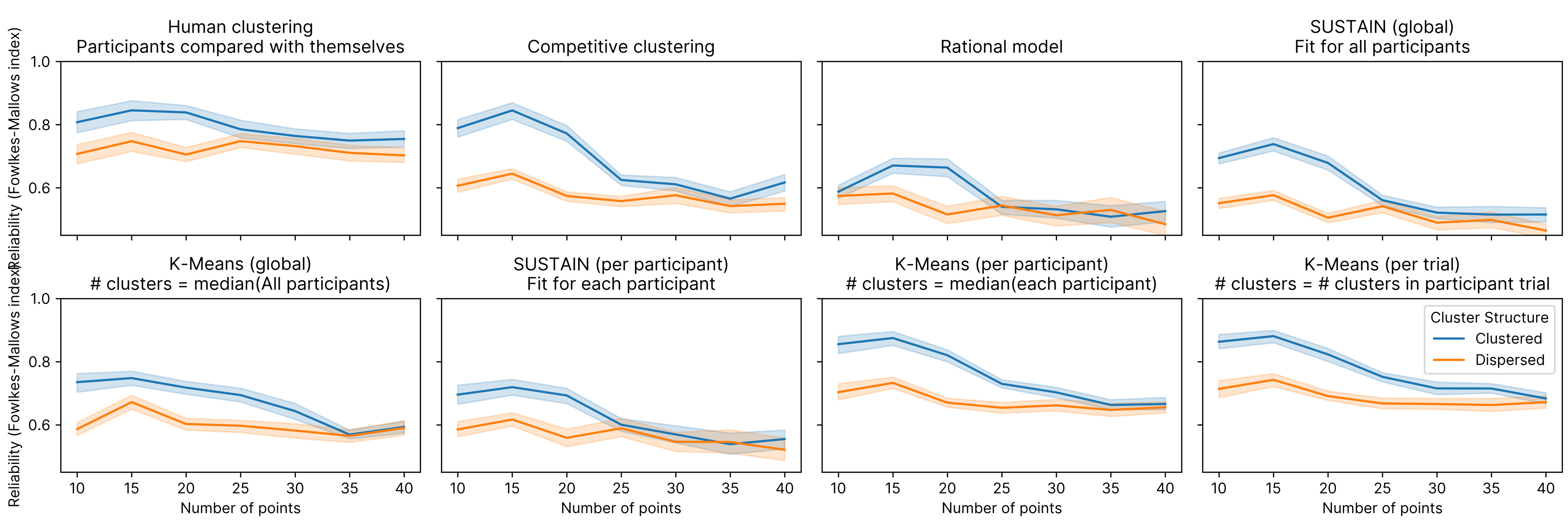
- Compared the model to the **Rational model**, **SUSTAIN**, and **K-Means**.

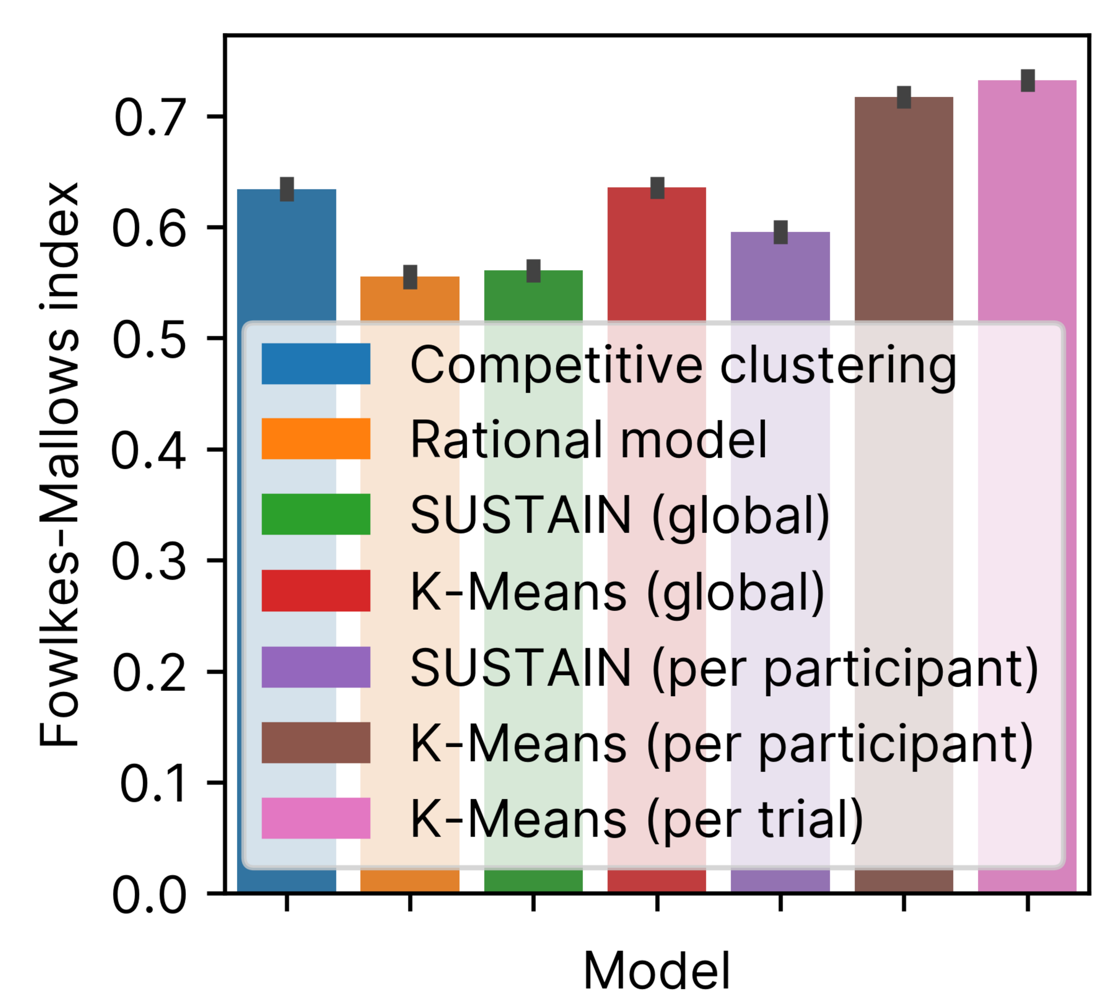
RESULTS & DISCUSSION

Analysis: The similarity of two clusterings was determined using the Fowlkes-Mallows (FM) index, for which 1 indicates an exact match. It is defined as:

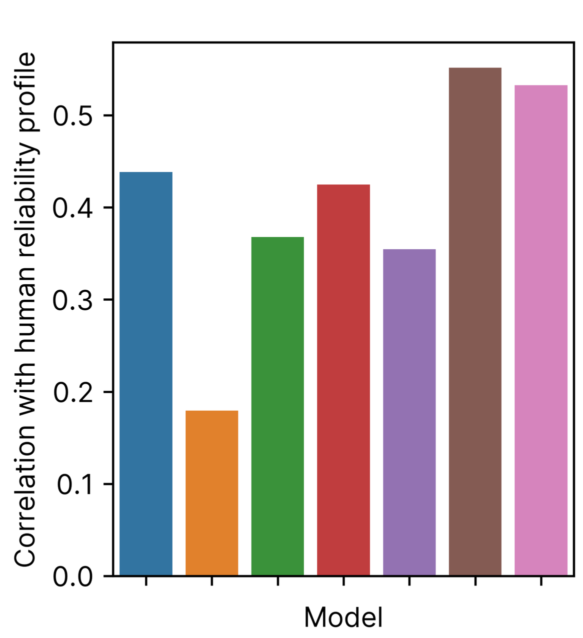
$$\mathrm{FM} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \cdot \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \text{ where}$$

- **TP**: True positive
- **FP**: False positive
- **FN**: False negative





- People's clusterings of the same stimulus were very similar to each other, suggesting the usage of a consistent algorithm / strategy.
- People were more reliable for clustered compared to dispersed stimuli.
- All models were able to fit human data well (FM > 0.54) and show the same pattern of reliability as humans, showing their viability as cognitive models of visual clustering.



- Of the cognitive models, the competitive clustering model was the best at capturing the differences in reliability across Number of Points and Cluster Structure as shown by humans.
- The Rational model was not able to capture the human performance profile as well as the other models.
- K-Means, fit per-participant and per-trial, was the best at capturing the human performance profile of the participants.

- The competitive clustering model performed the best of all cognitive models at predicting participants' clusters (i.e., generated the most similar clusterings as evaluated by the Fowlkes-Mallows Index).
- SUSTAIN (fit per participant) performed second best, followed by the Rational model and the SUSTAIN (global) model.
- However, K-Means, especially with number of clusters fit per participant or per trial, was the best at predicting participants' clusters.

REFERENCES

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