

# A Bayesian Implementation of the Circular Drift Diffusion Model

MathPsych, 2023

Adriana F. Chávez De la Peña, Manuel Villarreal,  
Michael D. Lee and Joachim Vandekerckhove

University of California, Irvine

# Overview

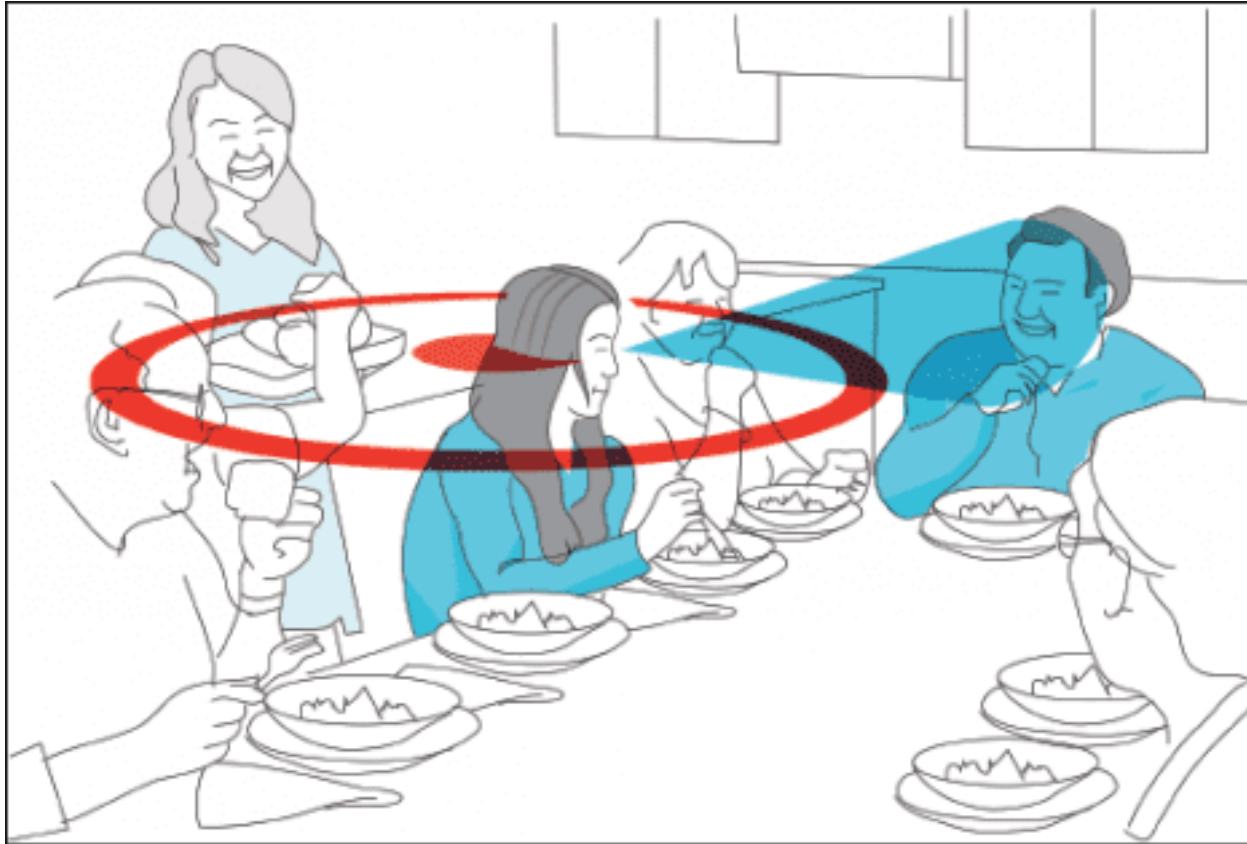
- The Circular Drift Diffusion Model (CDDM) is an extension of the drift-diffusion model to decision tasks with a circular decision space.
- We developed a custom JAGS module that allows for the implementations of the CDDM in a Bayesian framework.
- We demonstrate the adequacy of our CDDM module in simulation studies.
- We illustrate the advantages of our Bayesian implementation by revisiting publicly available data from a continuous orientation judgment task.

# Decisions on a circle

# Color identification

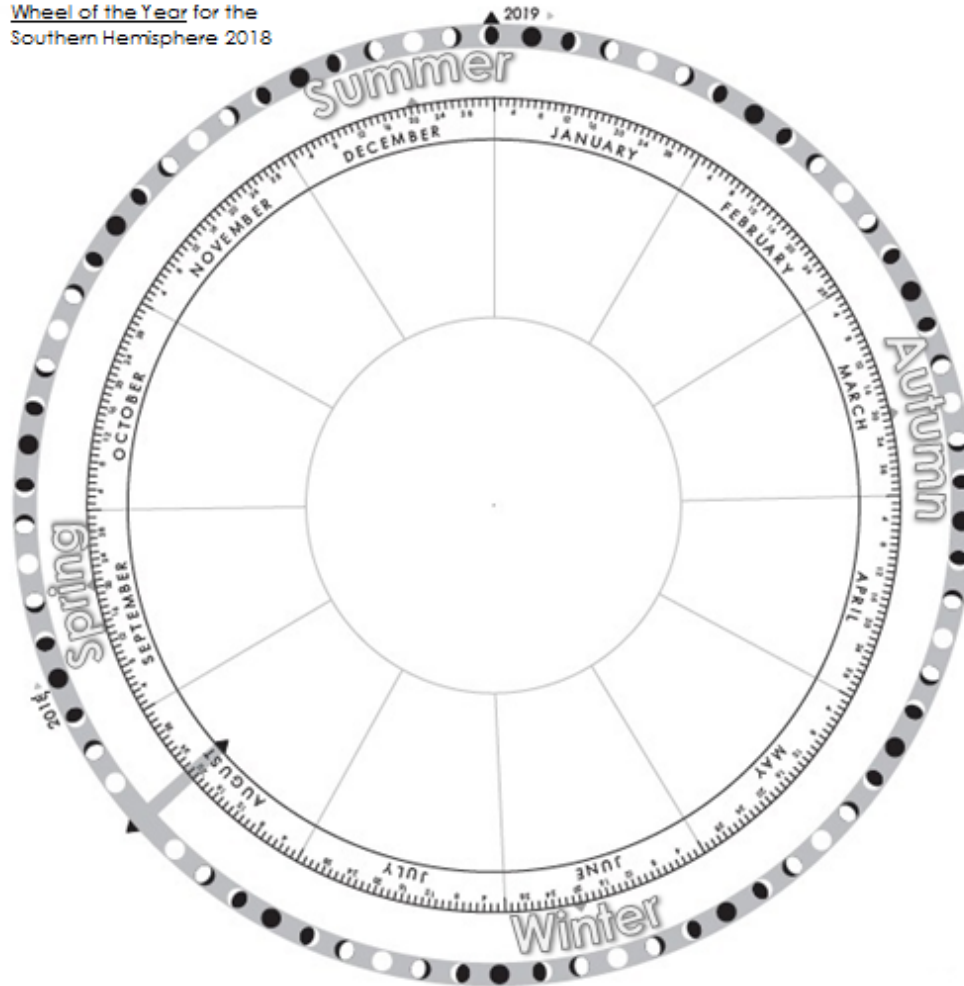


# Spatial location of sound



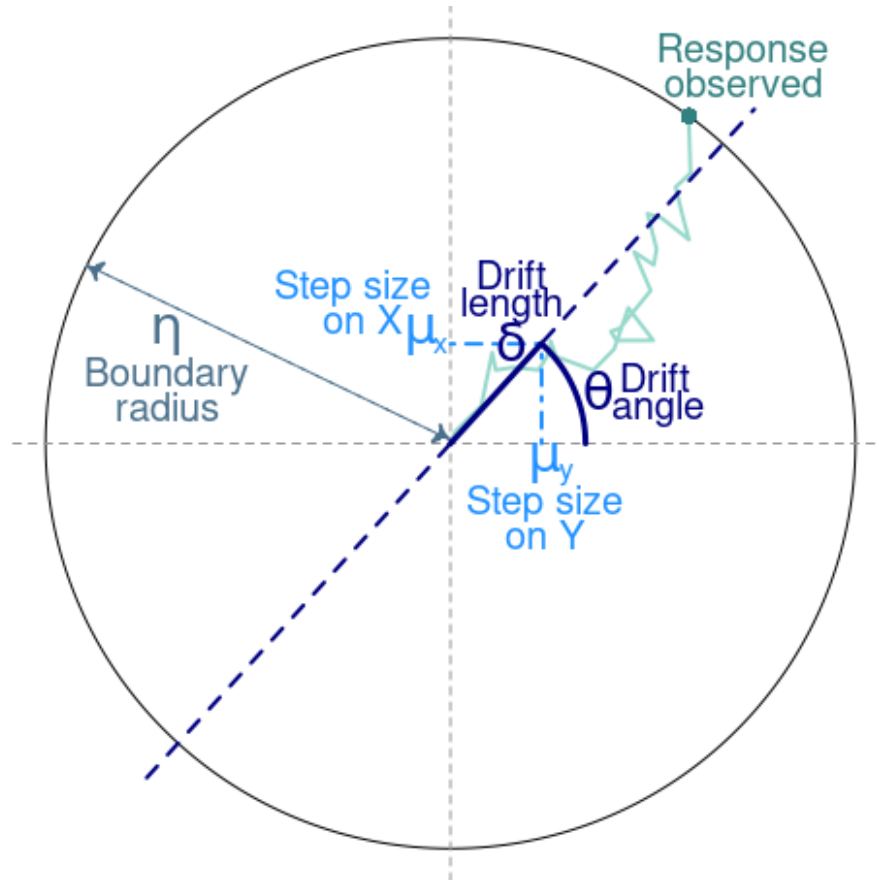
# Cyclic events

Wheel of the Year for the  
Southern Hemisphere 2018



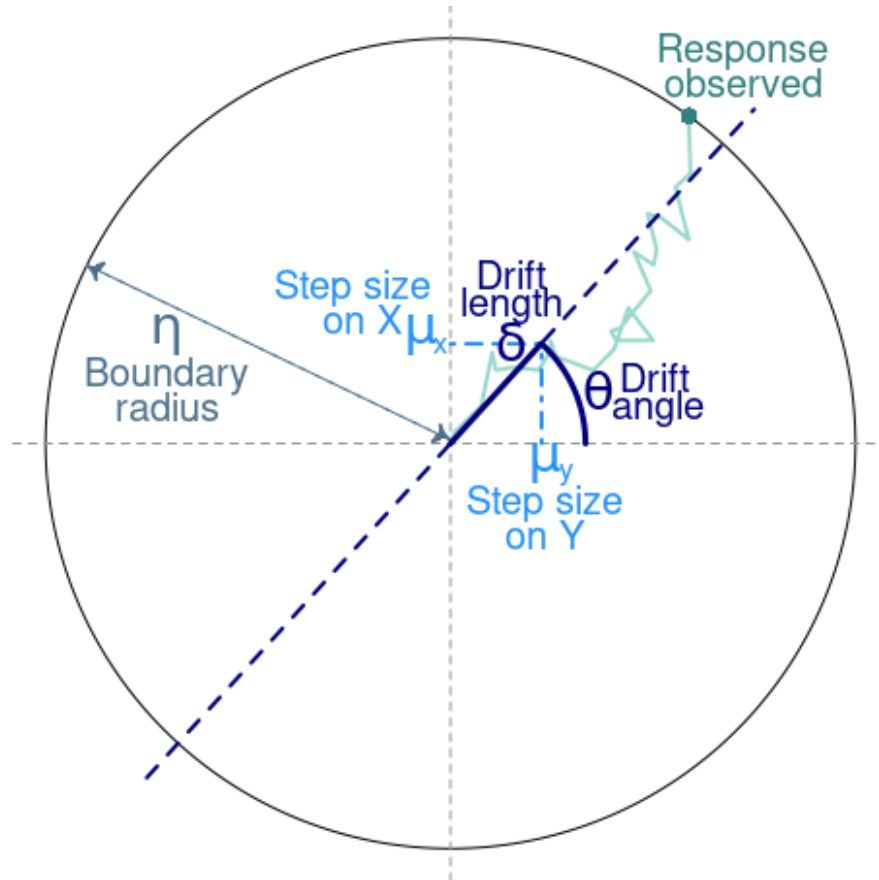
# The Circular Drift Diffusion Model (CDDM)

# Circular Drift Diffusion Model



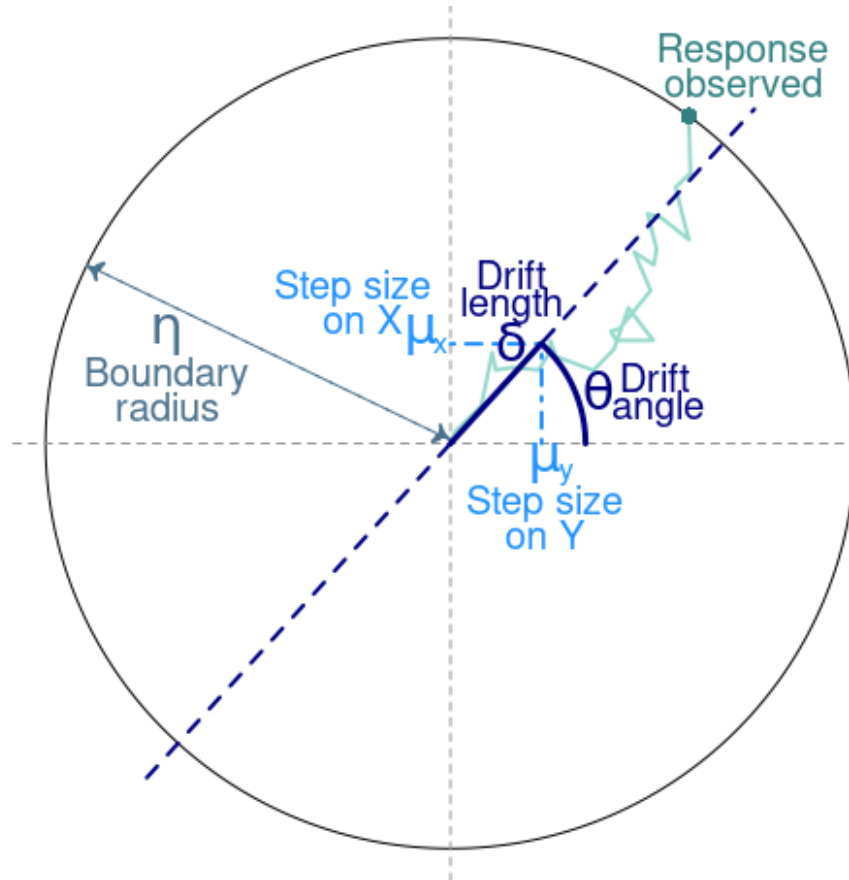


# Circular Drift Diffusion Model



- Nondecision time ( $\tau$ ): Visual encoding and motor control.
- Boundary radius ( $\eta$ ): Criterion to be reached to make a decision.

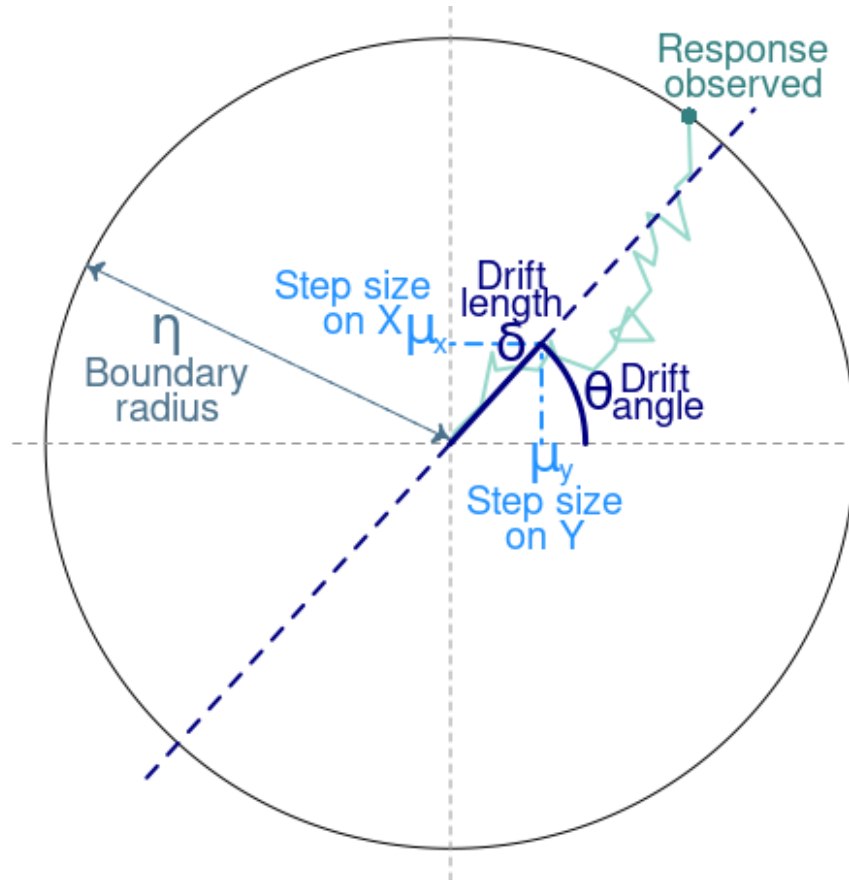
# Circular Drift Diffusion Model



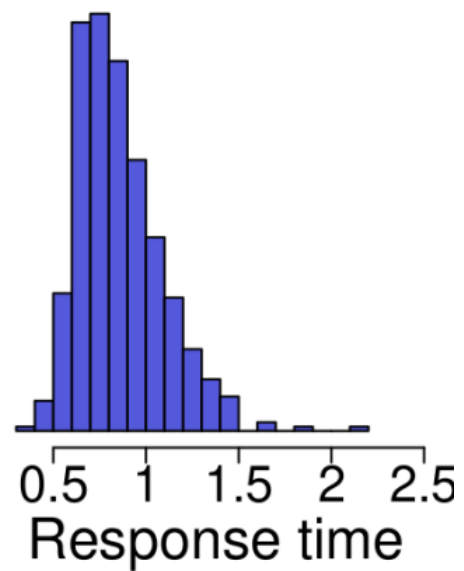
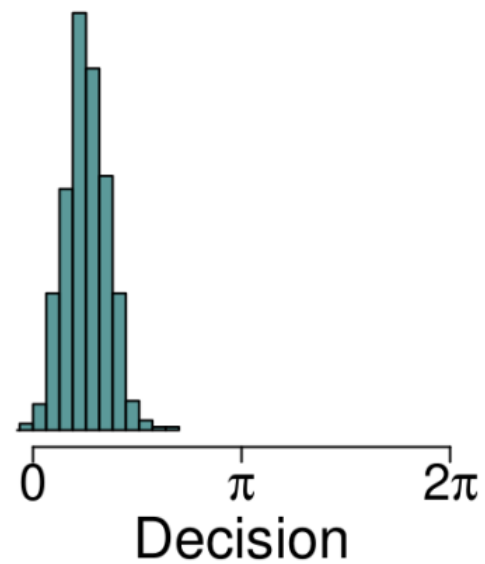
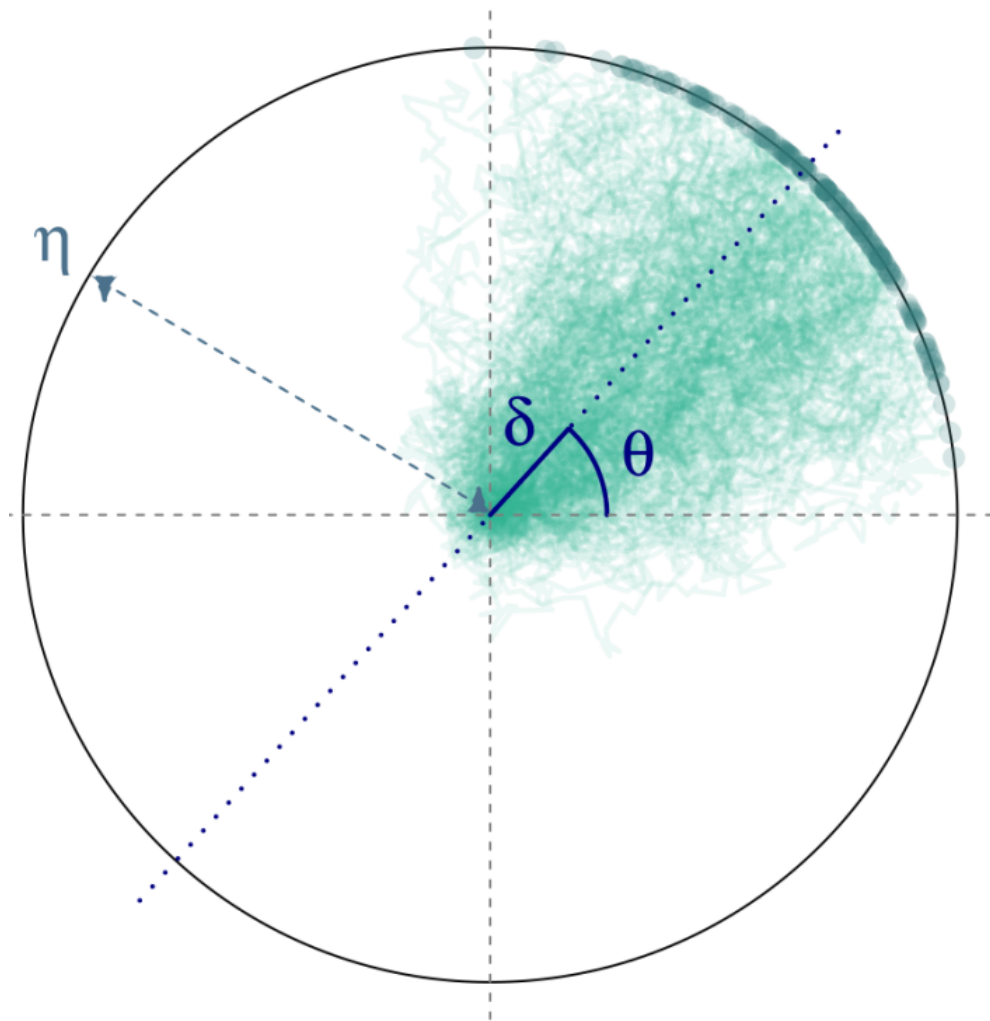
- Nondecision time ( $\tau$ ): Visual encoding and motor control.
- Boundary radius ( $\eta$ ): Criterion to be reached to make a decision.
- Mean step-size on x-axis ( $\mu_x$ ).
- Mean step-size on Y-axis ( $\mu_y$ ).

$$\mu = \{\mu_x, \mu_y\}$$

# Circular Drift Diffusion Model



- Nondecision time ( $\tau$ ): Visual encoding and motor control.
- Boundary radius ( $\eta$ ): Criterion to be reached to make a decision.
- Drift angle ( $\theta$ ): Direction of stimulus evidence.
- Drift length ( $\delta$ ): Speed of information processing .



# Implementing the CDDM module in JAGS

# CDDM module in JAGS

## Polar coordinate implementation

```
for (i in 1:N) {  
  X[1:2,i] ~ dcddmpolar(delta, theta, eta, tau)  
}
```

## Cartesian coordinate implementation

```
for (i in 1:N) {  
  X[1:2,i] ~ dcddmcartn(mux, muy, eta, tau)  
}
```

<https://github.com/joachimvandekerckhove/jags-cddm>

# Parameter recovery

$$\eta \in \{1.5, 2.0, 2.5\}$$

$$\tau \in \{0.1, 0.2, 0.3\}$$

## Cartesian implementation

$$\mu_x \in \{-0.5, 0, 0.5, 1\}$$

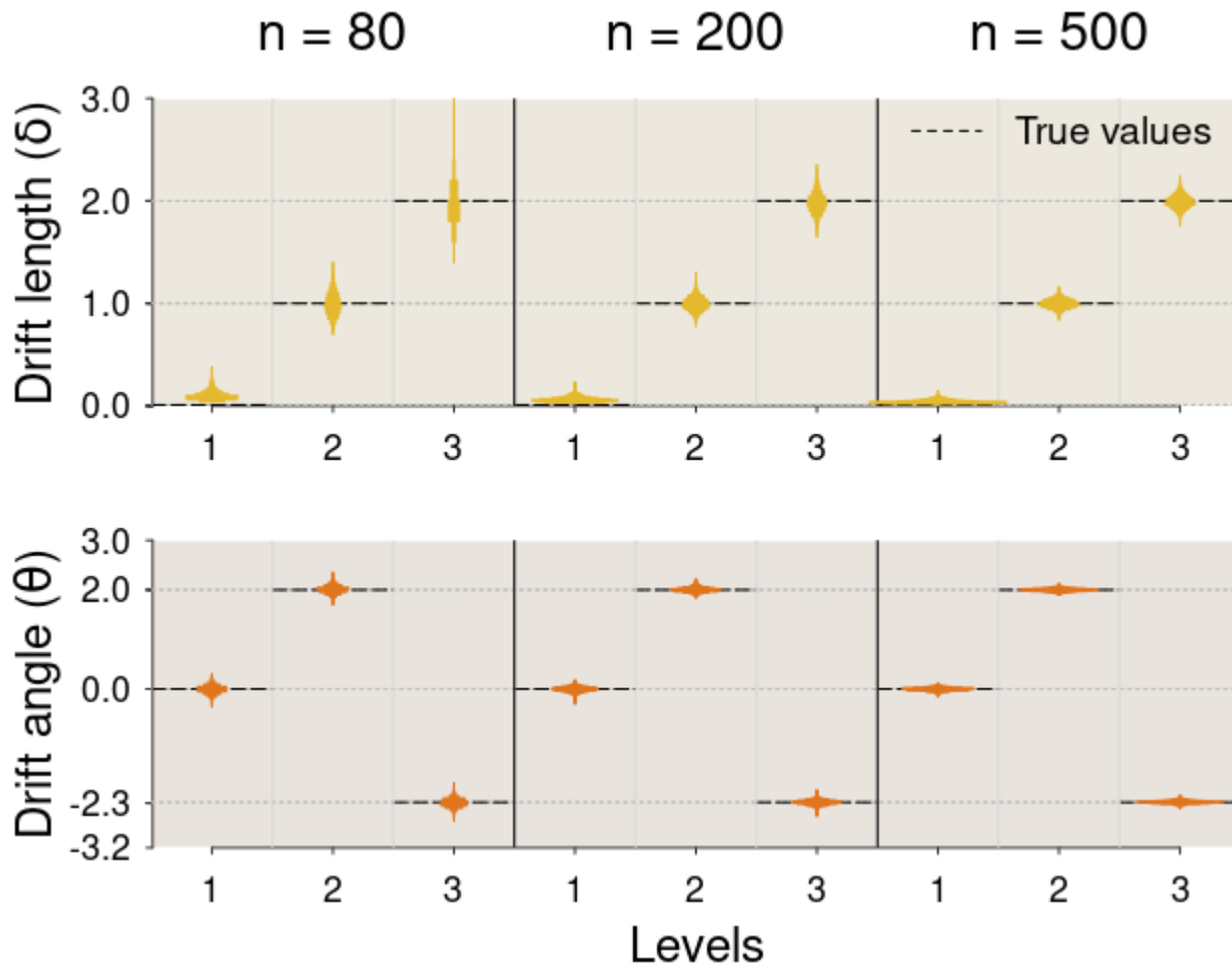
$$\mu_y \in \{-1, -0.5, 0, 0.5\}$$

## Polar implementation

$$\delta \in \{0.01, 1.0, 2.0\}$$

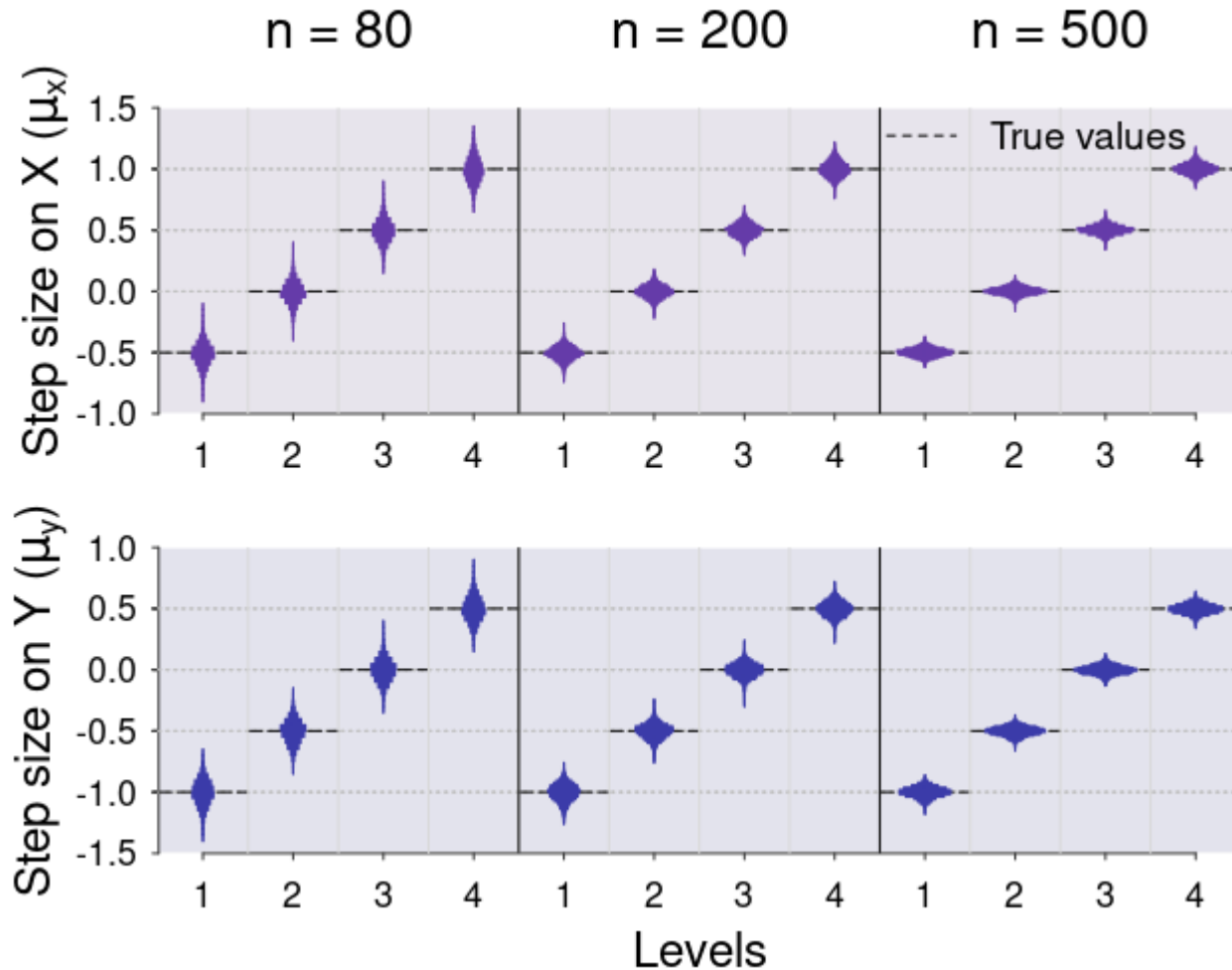
$$\theta \in \{0.0, 2.0, 4.0\}$$

# Parameter recovery

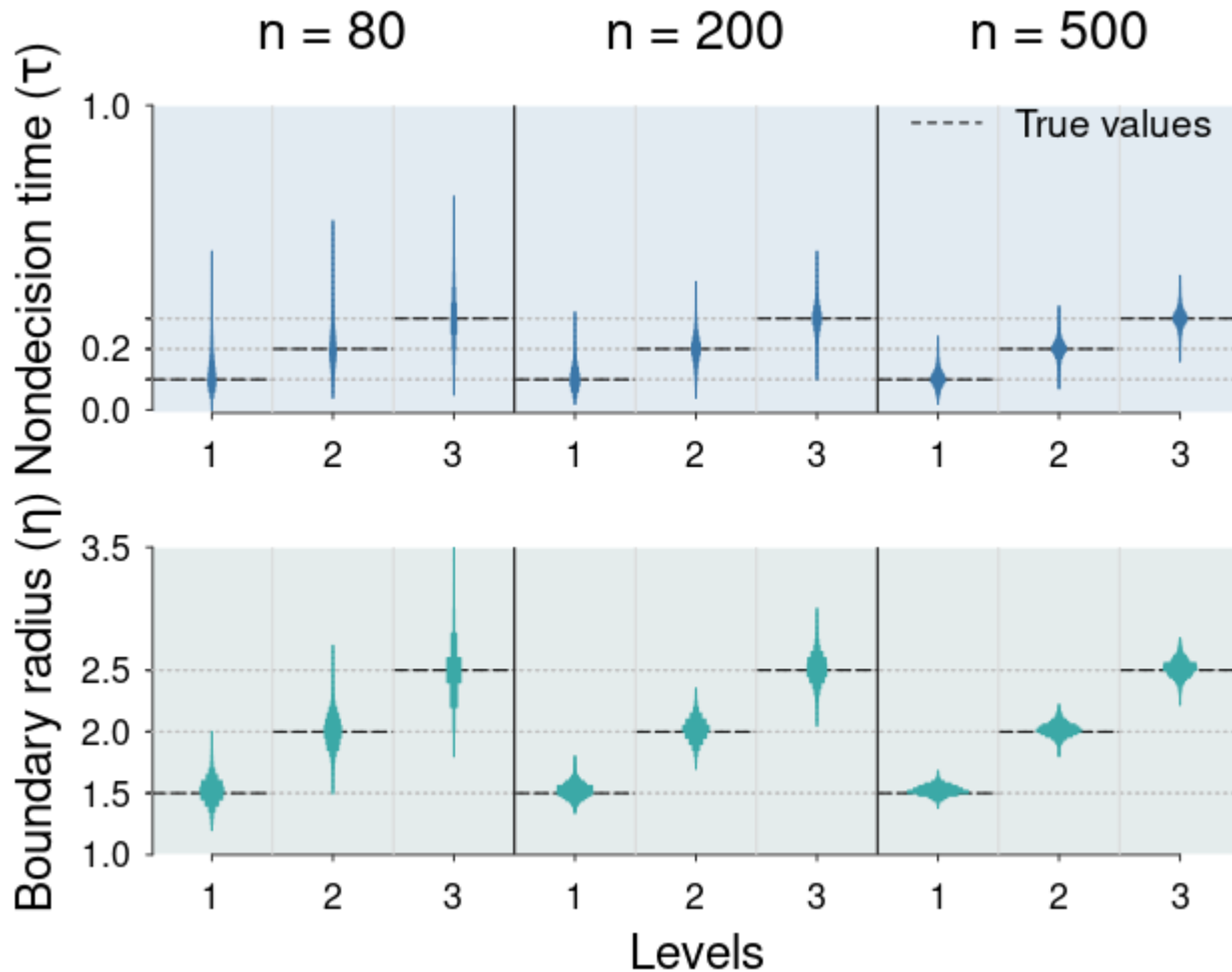




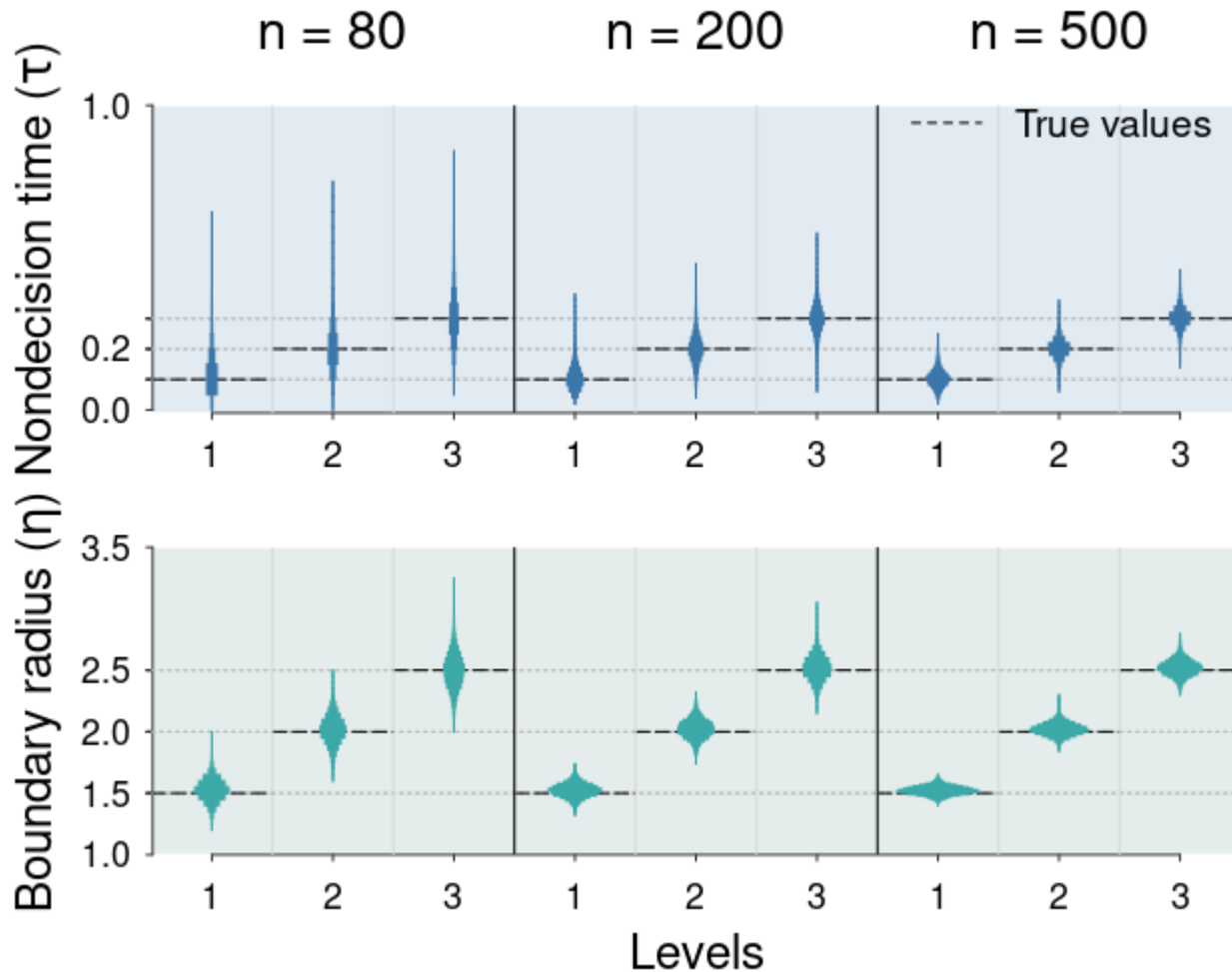
# Parameter recovery



# Parameter recovery



# Parameter recovery



# Application on real data

# Open data

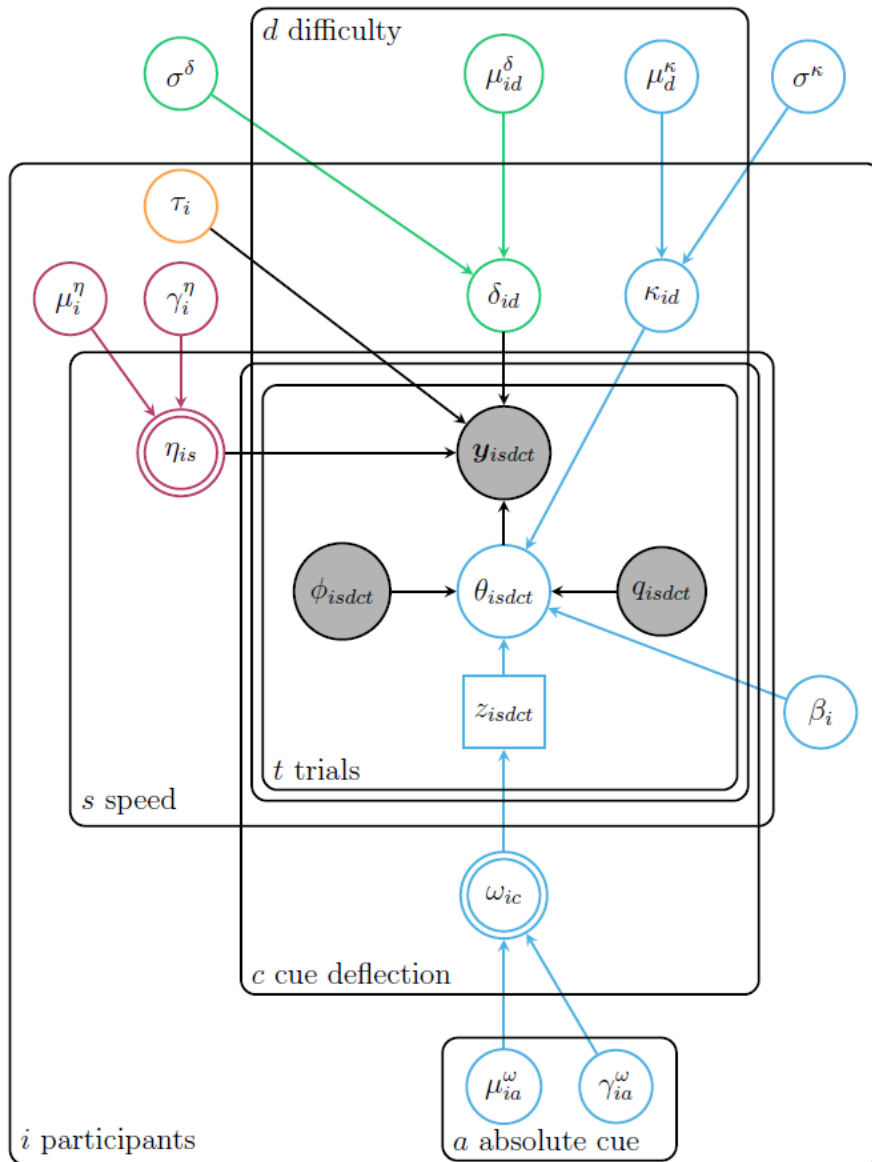
- Data presented by Peter Kvam (2019).
- Perceptual study where participants produce continuous orientation judgments.
- Task manipulations:
  1. Difficulty levels.
  2. Accuracy vs Speed instructions.
  3. Cue reliability variations.

# Task description

- **Stimuli:** A sequence of Gabor patches sampled from a normal distribution.
- **Main instruction:** Indicate the true mean orientation of the patches presented by clicking any point on the circumference of a circle.
- **2 x 2 factorial design:** Speed vs Accuracy - Cued vs Uncued presentation.
- **Three levels of difficulty:** 15, 30 and 45 degrees of standard deviation.

# Research questions

- 1.- Are participants more cautious to respond when they are instructed to prioritize accuracy over speed? ( $\eta$ )
- 2.- Does information processing speed change with task difficulty? ( $\delta$ )
- 3.- Does the consistency of the stimulus information decrease as a function of task difficulty?
- 4.- Do different degrees of cue deflections have an impact on how likely participants are to ignore the cue while making a decision?

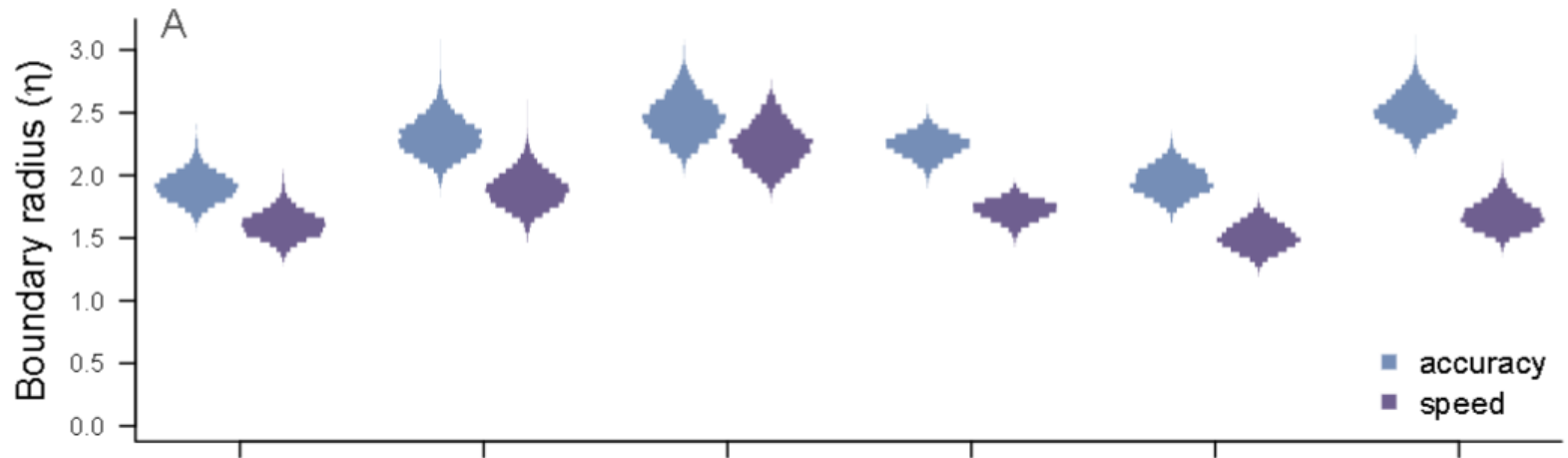


$$\begin{aligned}
 \mu_i^\eta &\sim \text{Gaussian}(0, 1) \\
 \gamma_i^\eta &\sim \text{Gaussian}(0, 1)T(0, \infty) \\
 \eta_{is} &= \begin{cases} \exp(\mu_i^\eta + \gamma_i^\eta/2) & \text{if } s = \text{accuracy} \\ \exp(\mu_i^\eta - \gamma_i^\eta/2) & \text{if } s = \text{speed} \end{cases} \\
 \tau_i &\sim \text{uniform}(0, \min y_{i1}) \\
 \mu_d^\delta &\sim \text{Gaussian}(0, 1) \\
 \sigma^\delta &\sim \text{uniform}(0, 1) \\
 \delta_{id} &\sim \text{log-Gaussian}\left(\mu_d^\delta, \frac{1}{(\sigma^\delta)^2}\right) \\
 \mu_d^\kappa &\sim \text{Gaussian}(0, 1) \\
 \sigma^\kappa &\sim \text{uniform}(0, 4) \\
 \kappa_{id} &\sim \text{log-Gaussian}\left(\mu_d^\kappa, \frac{1}{(\sigma^\kappa)^2}\right) \\
 \mu_{ia}^\omega &\sim \text{Gaussian}(0, 1) \\
 \gamma_{ia}^\omega &\sim \text{Gaussian}(0, 1) \\
 \frac{\omega_{ic}}{1 - \omega_{ic}} &= \begin{cases} \exp\left(\mu_{ia}^\omega + \frac{\gamma_{ia}^\omega}{2}\right) & \text{if } c > 0 \\ \exp\left(\mu_{ia}^\omega - \frac{\gamma_{ia}^\omega}{2}\right) & \text{if } c < 0 \\ \exp(\mu_{ia}^\omega) & \text{if } c = 0 \end{cases} \\
 z_{isdct} &\sim \text{Bernoulli}(\omega_{ic}) \\
 \beta_i &\sim \text{uniform}(0, 1) \\
 \theta_{isdct} &\sim \begin{cases} \text{Gaussian}(\phi_{isdct}, \kappa_{id}) & \text{if } z_{isdct} = 0 \\ \text{Gaussian}(q_{isdct}, \beta_i \kappa_{id}) & \text{if } z_{isdct} = 1 \end{cases} \\
 y_{isdct} &\sim \text{CDDM}_o(\delta_{id}, \eta_{is}, \tau_i, \text{mod}(\theta_{isdct}, 2\pi))
 \end{aligned}$$



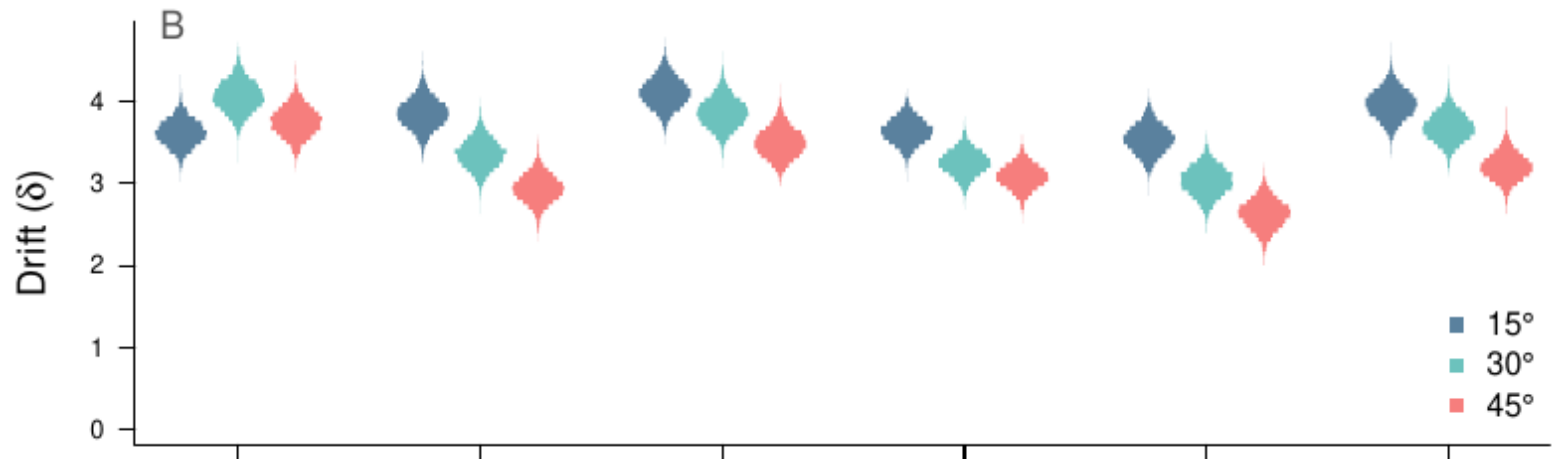
# Test 1.

Are participants more cautious to respond in the Accuracy condition?



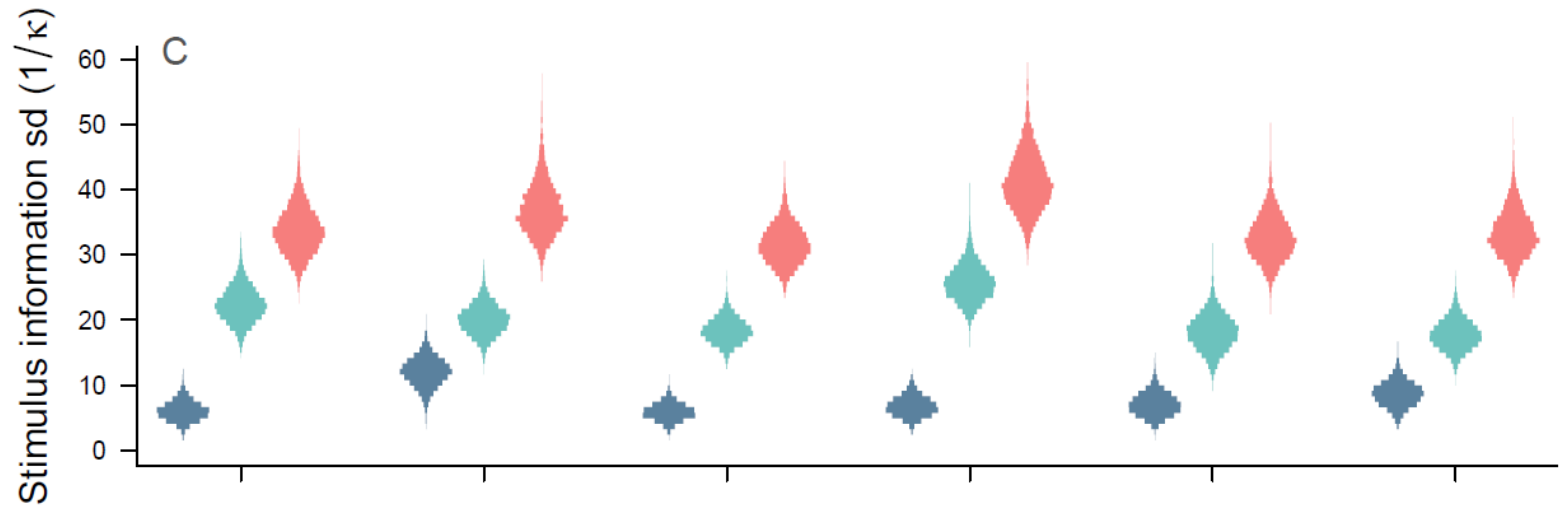
# Test 2.

Does information processing speed decrease as task difficulty increases?



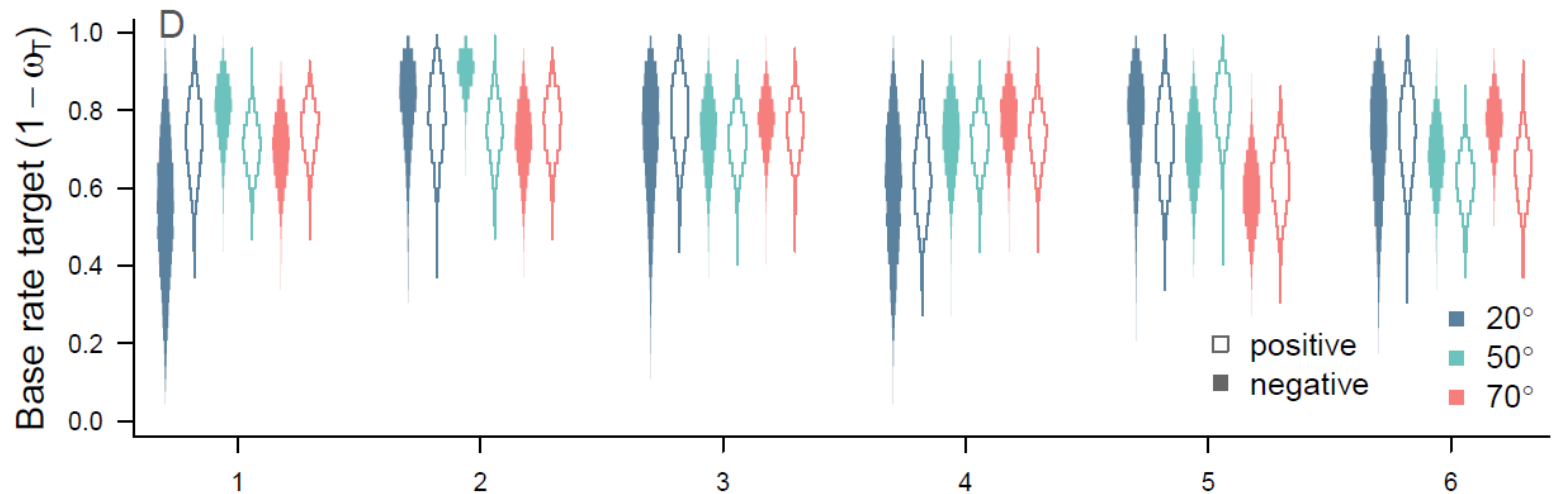
# Test 3.

Does the consistency of the stimulus information change as a function of task difficulty?



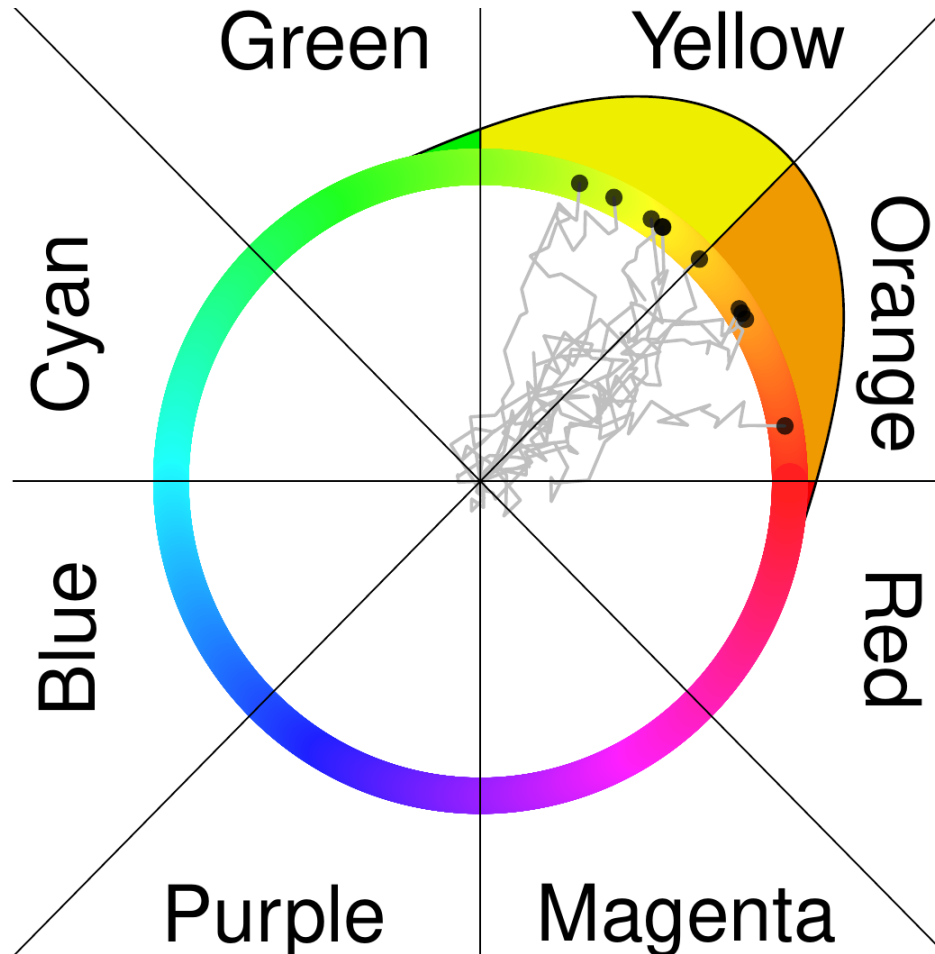
# Test 4.

Do different cue deflections change how likely participants are to ignore the cue orientation while making a decision?

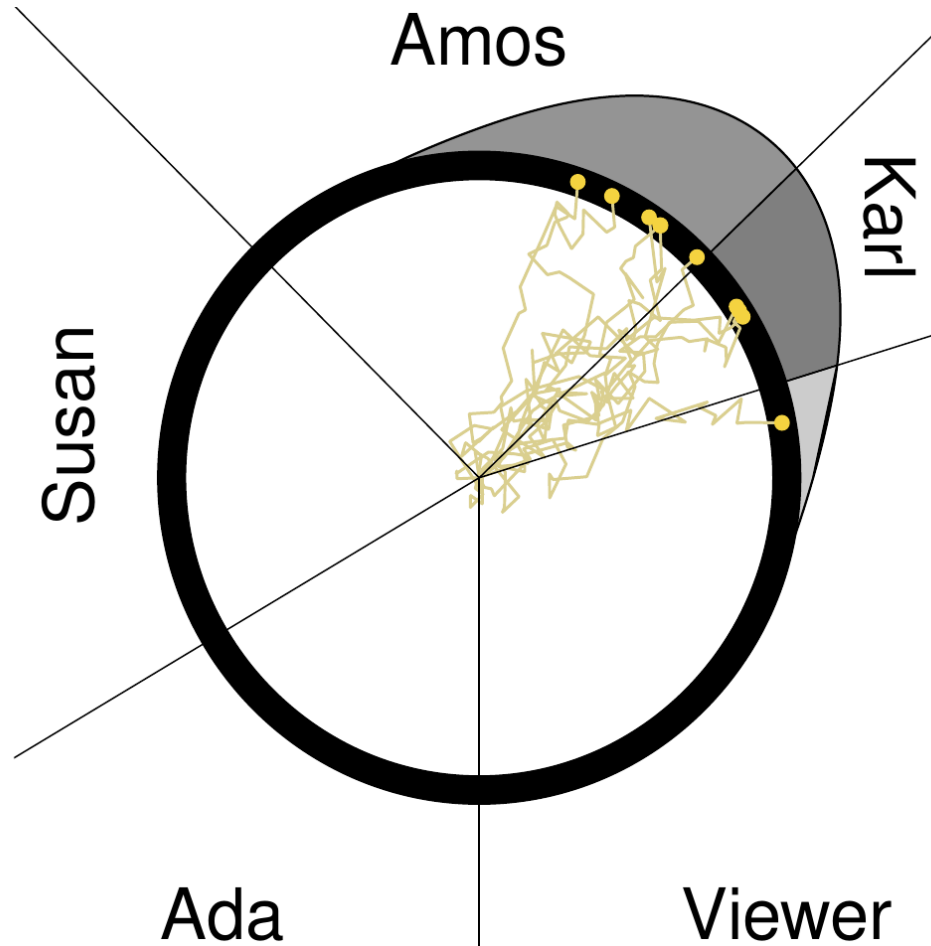


# Future work

# Discrete extension of the CDDM



# Discrete extension of the CDDM



# Acknowledgements





**Thank you!**