Dissociating Implicit Versus Explicit Motor Decision-making During a Sensorimotor Adaptation Task

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Introduction

- The sensorimotor system is highly sensitive to externally-generated errors (EGE), while ignoring internally-generated errors (IGE) (Ranjan & Smith 2018, 2022; Kim et al, 2025)
- EGEs 1.5 times typical IGE are required to consciously report the presence of EGE (Gaffin-Cahn et al, 2019)
- These inferences have never been examined under one study

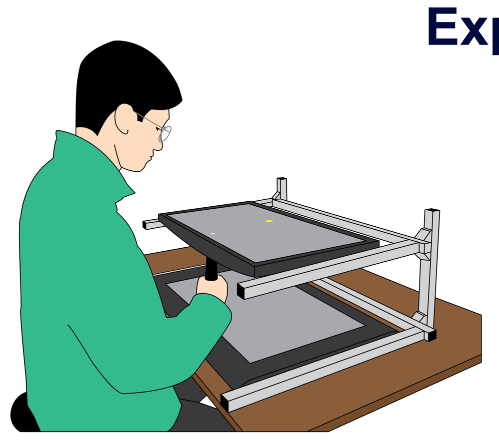
The purpose of this study is to examine the computational principles underlying implicit and explicit error detection.

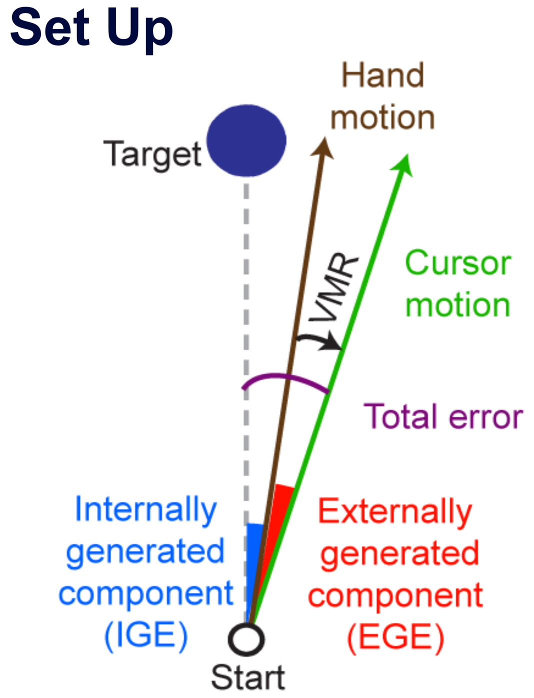
Takeaways

- Findings support Bayesian causal inference as a framework underlying both implicit and explicit error detection.
- Task-dependent changes in proprioceptive uncertainty help explain decoupling between implicit and explicit processes.
- PIECE's performance suggests a shared set of computational principles for both perception and action.
- See also: http://motor-conference.org/openconf.php

Methods

Experimental Set Up

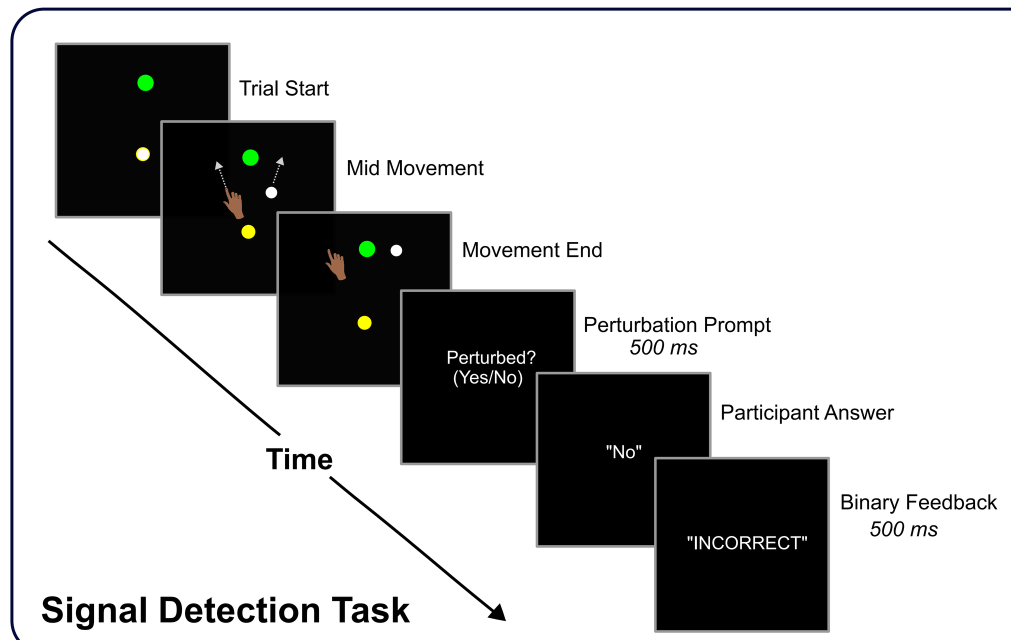




The experiment used a top-mounted screen and bottom tablet with the participant's hand hidden. The screen showed the cursor, start circle, target, and detection prompts, and participants responded using a mouse.

Ranjan & Smith 2018, 2022

Experimental Tasks



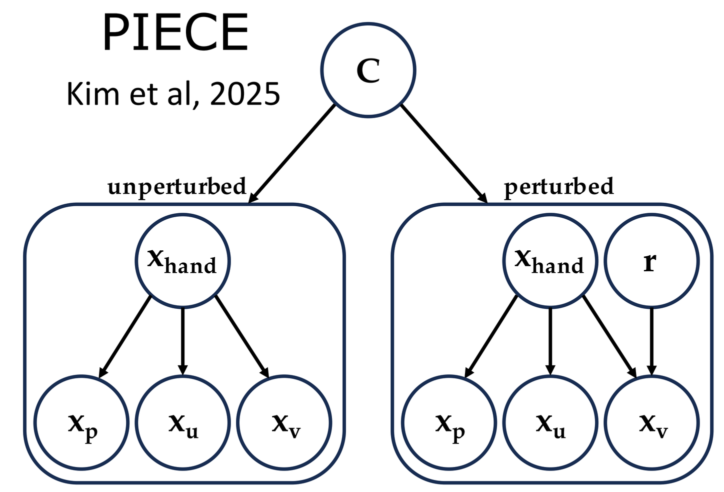
Signal Detection Task

Adaptation: Similar methods used as Kim et al (2025) but incorporated greater range of perturbations.

Signal Detection (Left): Participants made reaches to target and were asked whether they believed cursor feedback was perturbed.

Models of error detection

a



Combines proprioceptive (x_p), motor prediction (x_u) and visual (x_v) cues to form posterior on C, and uses this as weight on estimate of perturbation size.

$$p(C|x_v, x_p, x_u) = \frac{p(C)p(x_v, x_p, x_u|C)}{p(x_v, x_p, x_u)}$$

b

Gaffin-Cahn et al, 2019

VCO $\underbrace{|x_v - b|}_{e_t} > D_{\text{threshold}}$

Detects errors when difference between cursor and bias is large.

CO $\underbrace{|x_v - x_p|}_{e_t} > D_{\text{threshold}}$

Detects errors when difference between cursor and hand is large.

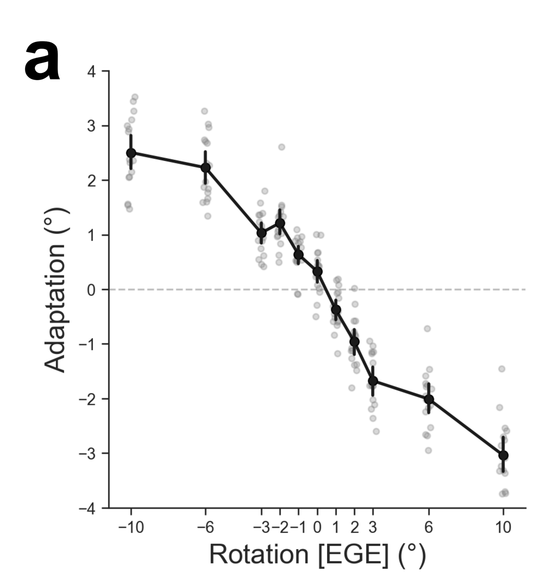
c

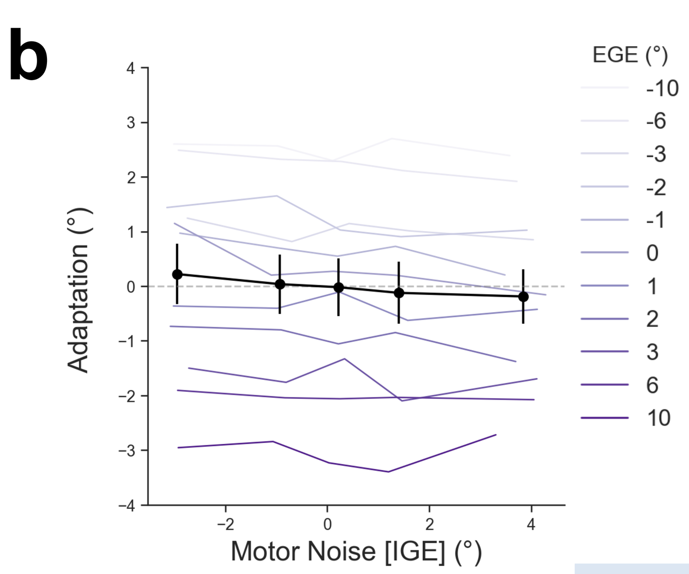
$$x_{hand}^{(t+1)} = \begin{cases} -\beta \cdot e_t + b + \varepsilon_m, & \text{if } |e_t| > D_{\text{threshold}} \\ b + \varepsilon_m, & \text{if } |e_t| \leq D_{\text{threshold}} \end{cases}$$

VCO and CO predict next-trial hand trajectory from previous trial's error.

Results

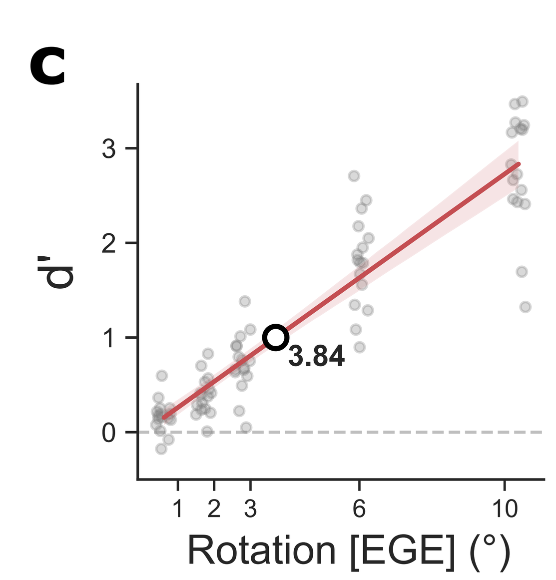
Dissociation between explicit and implicit detection

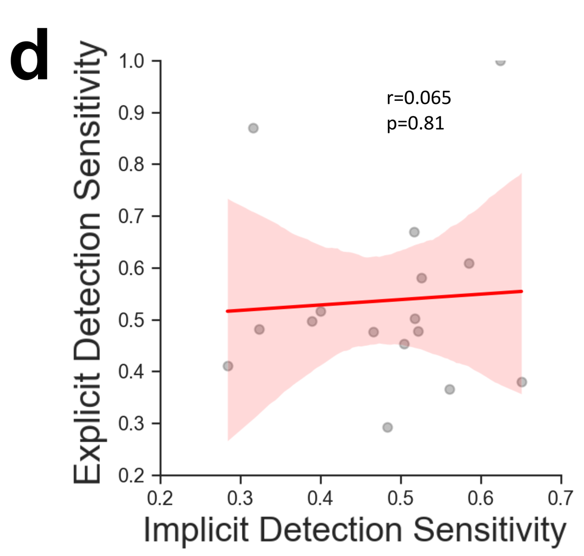




(a) Adaptation to EGE begins at 1° and saturates at 6°.

(b) Adaptation to IGE is constant across all IGE sizes.





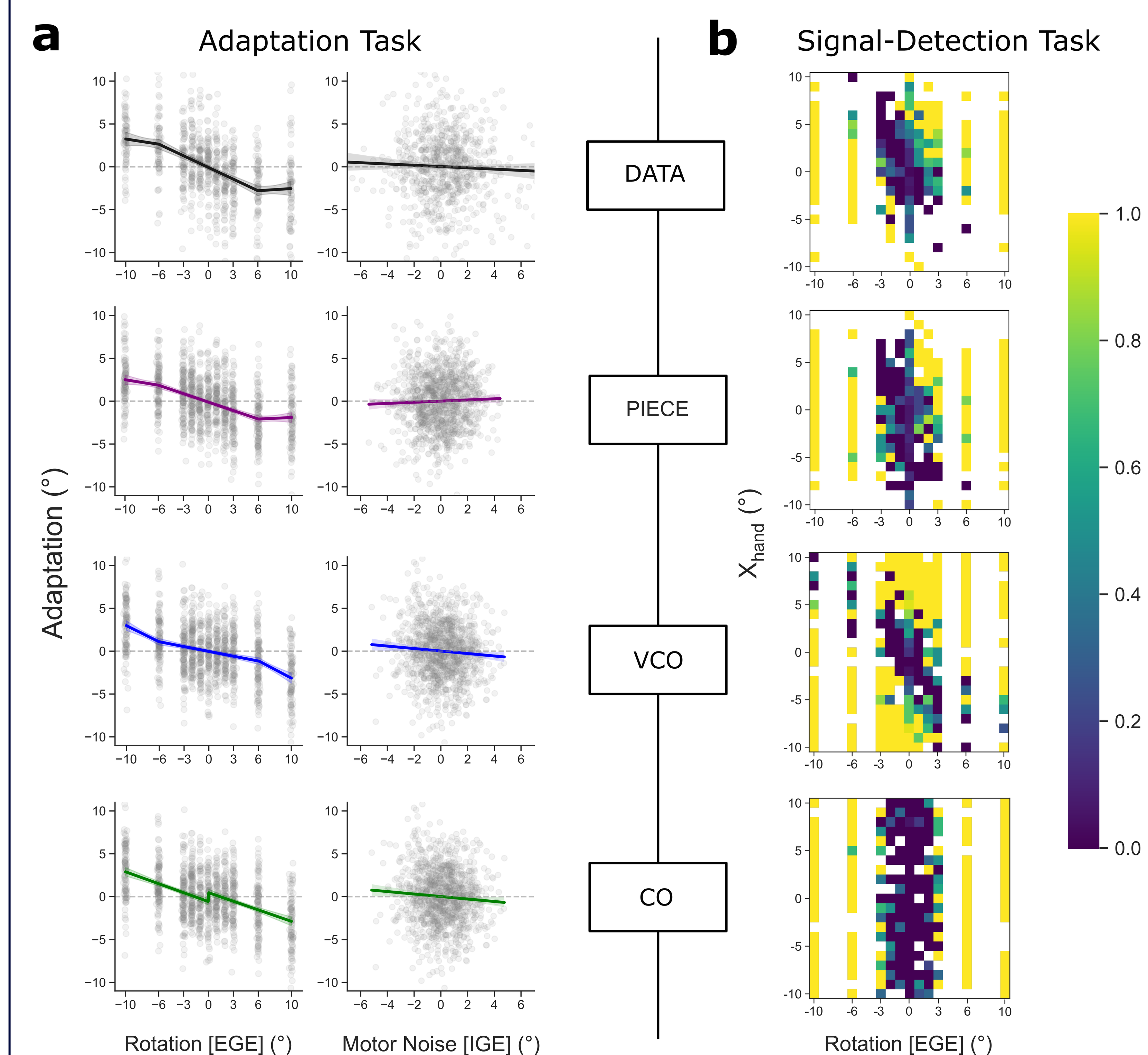
(c) In the Signal Detection Task, d' = 1 (detection threshold) occurs at 3.84°.

(d) Relating normalized implicit and explicit detection sensitivities (below), we see no relationship.

$$\text{Implicit} = \frac{|\beta_{EGE}|}{|\beta_{EGE}| + |\beta_{IGE}|}$$

$$\text{Explicit} = \frac{d'}{\max(d')}$$

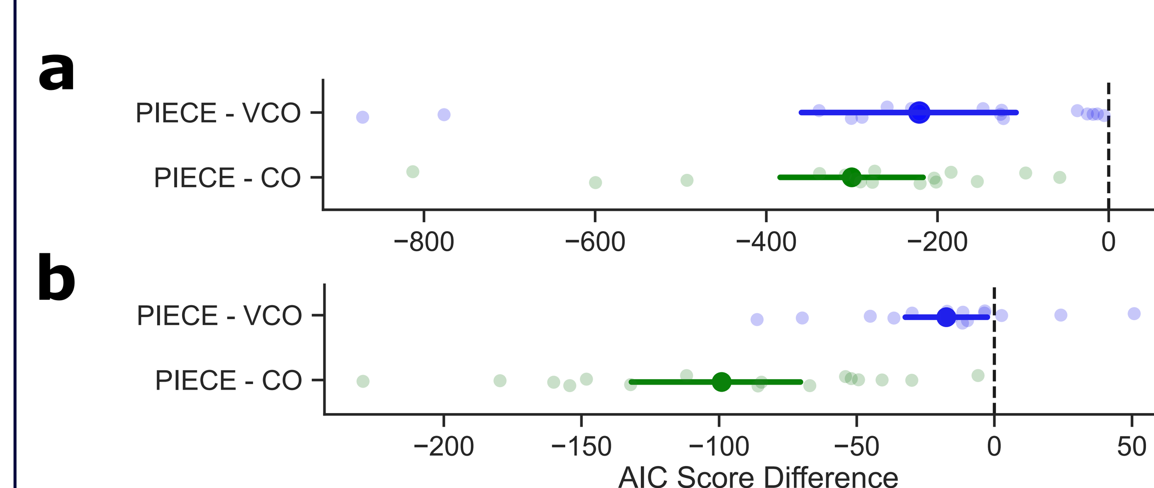
PIECE Best Fits Implicit and Explicit Detection



(a) Only the PIECE model accurately captures the combination of saturated adaptation to EGE and minimal adaptation to IGE.

(b) The PIECE model best captures the pattern of explicit error detection as a function of perturbation size and hand position.
Piecewise regression was used in (a), with shaded areas representing 95% CIs and dots representing individual trials.

Model Selection Favours PIECE



Direct comparisons of AIC scores from each model to PIECE for the **(a)** Adaptation Task and the **(b)** Signal-Detection Task.

Proprioceptive Uncertainty Different Between Tasks