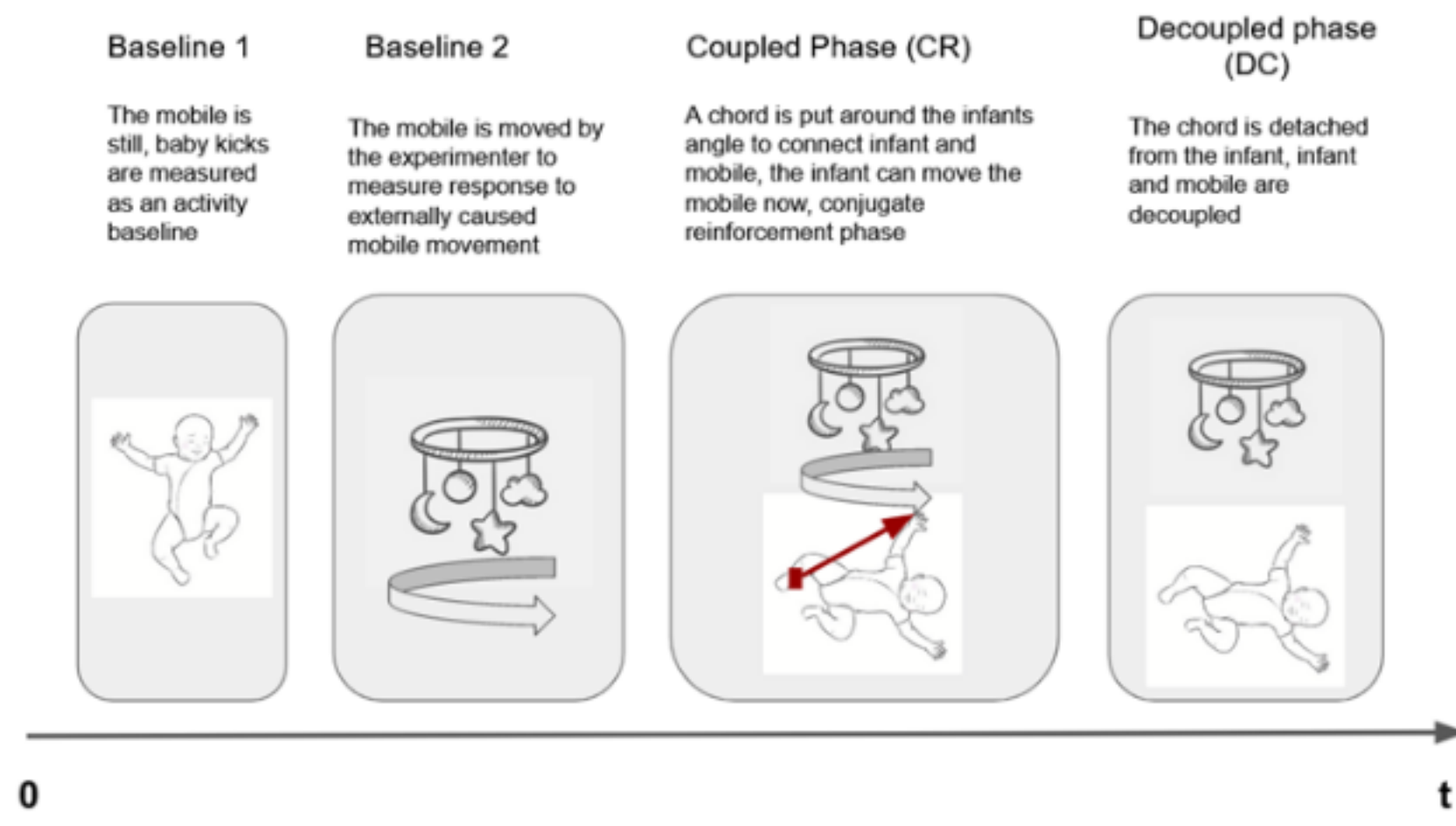


# Discovery of agency in action and stillness: an Active Inference model

## INTRODUCTION

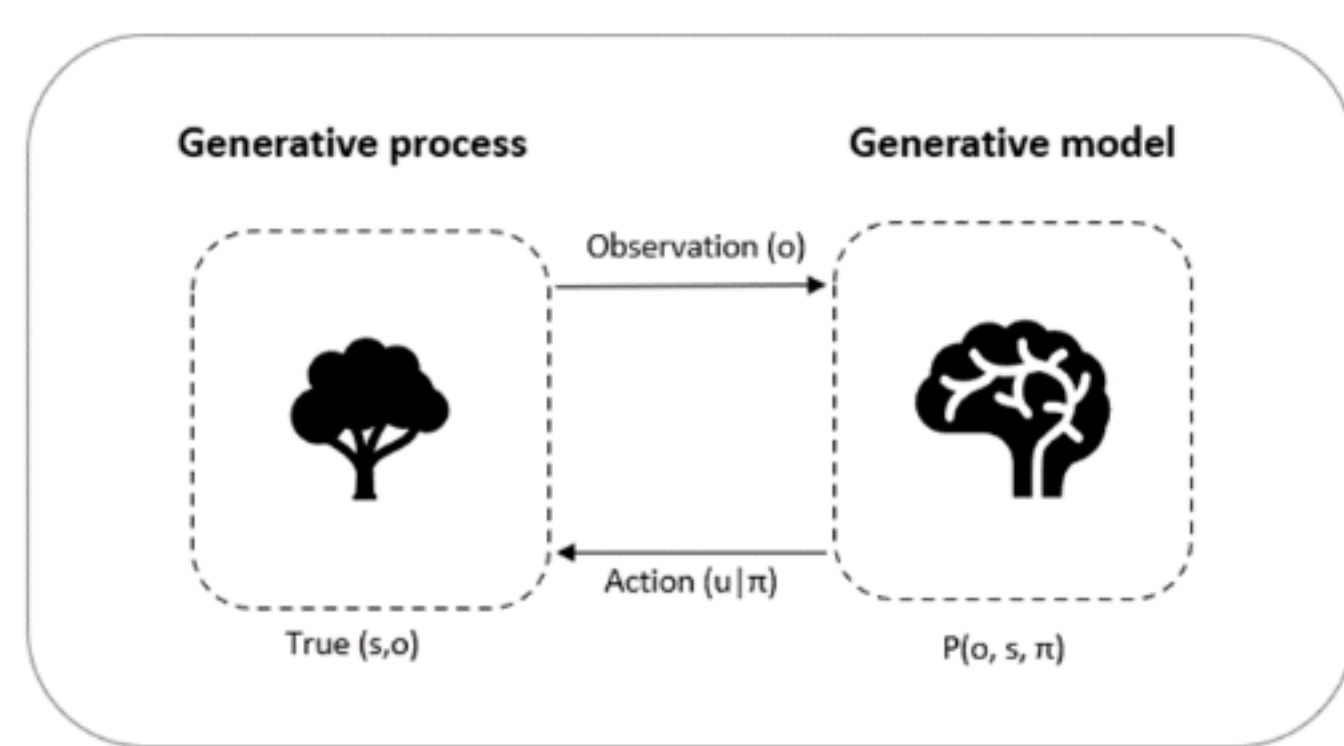
**How do infants discover that they can affect the world?** Mobile Conjugate Reinforcement (MCR) is a model paradigm to study a poorly understood but vital process: the emergence of **agency**, action towards an end [1, 2].

When one of their feet is tethered to a hanging mobile, infants can discover their ability to make the toy move. Increased kicking during infant~mobile interaction is classically interpreted as evidence that infant leg movements are linearly reinforced by mobile motion, which is assumed to be inherently rewarding [3].



Schematic representation of the four phases of the MCR experiment.

Alternatively, the proposed **predictive processing account** casts infants as actively seeking sensory states to resolve uncertainty about internal models of the external world and their own movements.



Coupling of action and perception in active inference - both action and perception are optimized by minimizing **free energy**

To explore the cognitive mechanisms underlying infants' developing agency, we propose an **active inference model of kicking** behavior during the MCR paradigm, which incorporates two primitive **aspects of agency**:

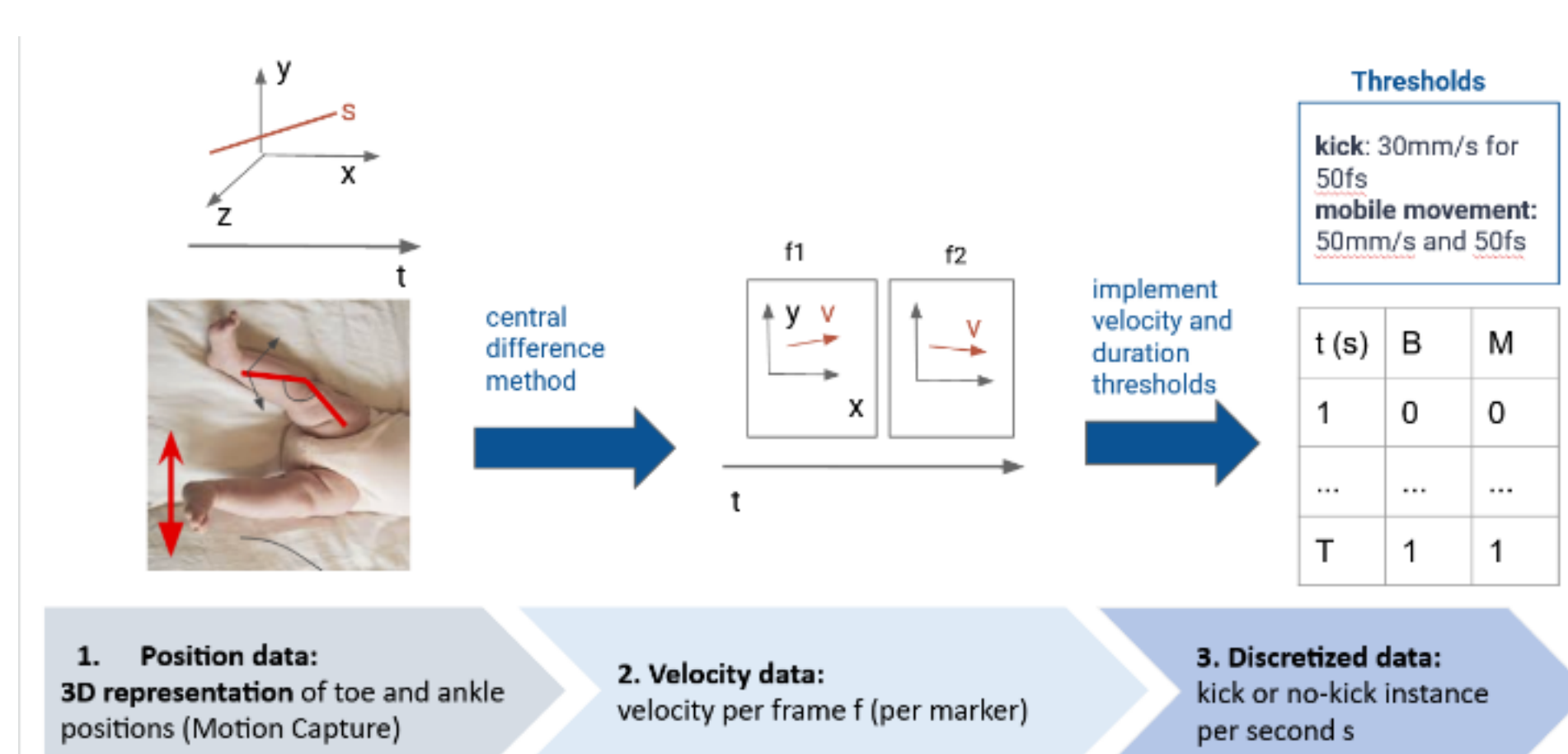
**perceptual learning**: associations between perceptions of self-movement and mobile-movement

**contingency learning**: associations between self-actions and mobile movement

We propose that the infant in the MCR setting is not merely responding to the extrinsic mobile stimulus but is displaying behavior driven by its **curiosity** about the world and itself [4].

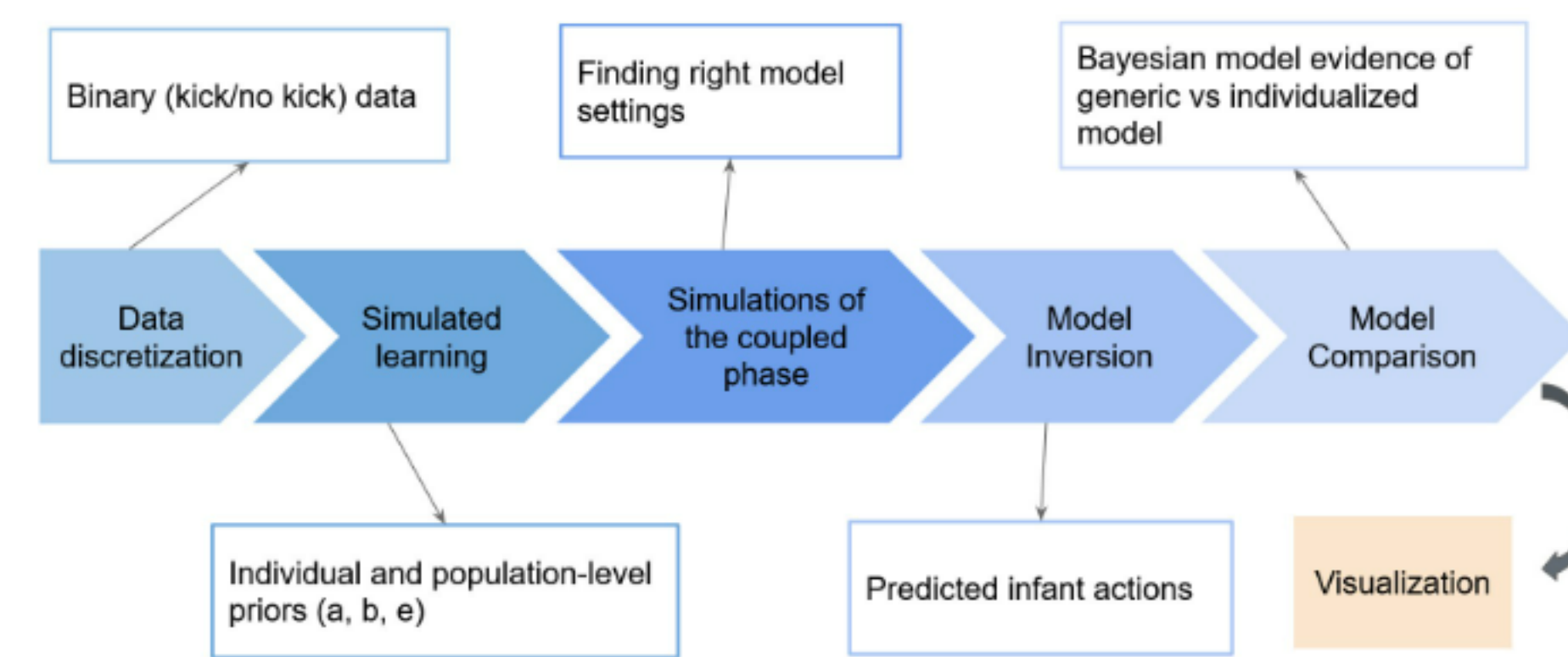
## METHODS

An MCR experiment was conducted by the FAU Human Brain & Behavior Lab with infants ( $n = 14$ ) aged 84-146 days, (median age = 97 days) [5]. Infant and mobile movement were recorded using Vicon 3D **motion capture** at 100 Hz with markers placed on the toes and ankles. The infant was positioned beneath a mobile (radius = 186.5 cm).

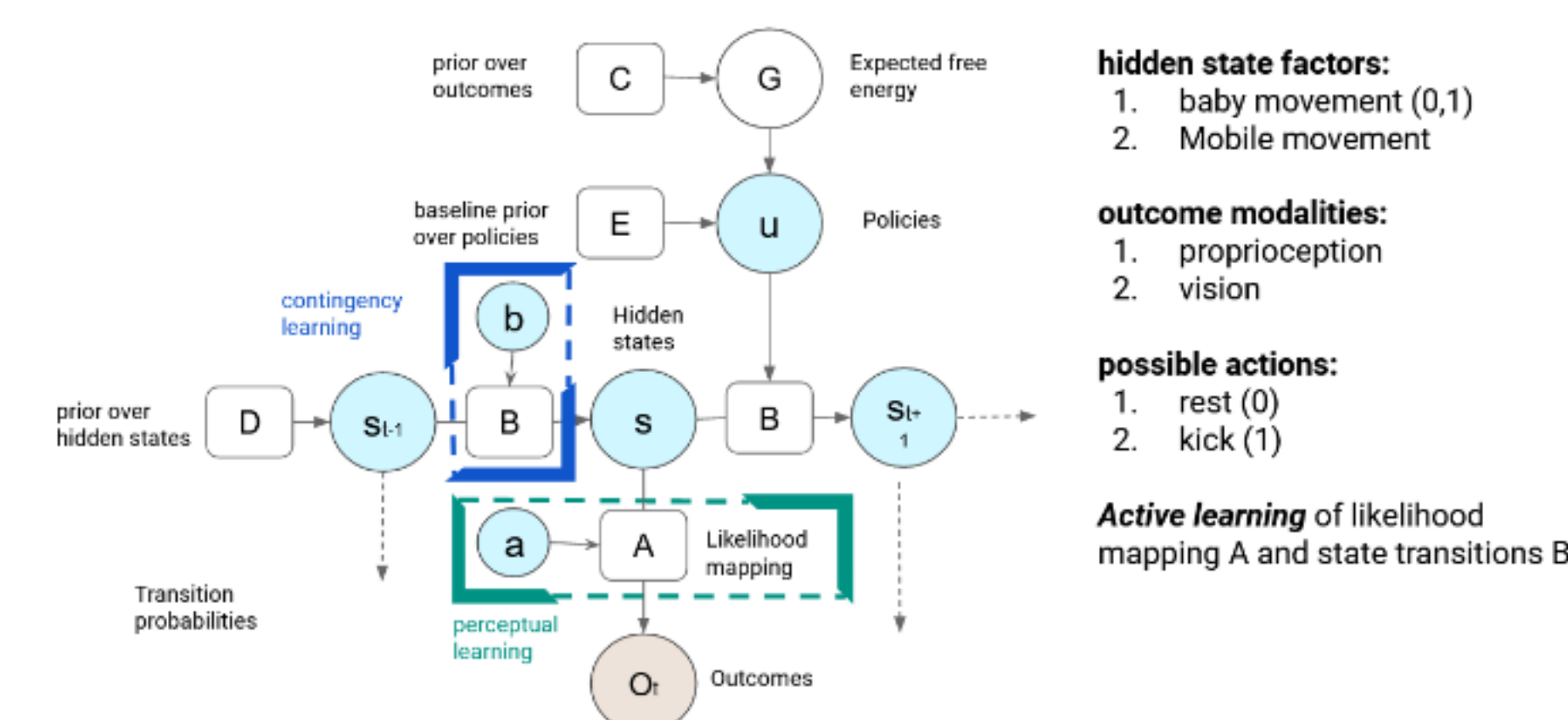


Data discretization procedure

## METHODS



A schematic representation of the modeling procedure



Bayesian network representation of state estimation and policy selection for the MCR active inference agent.

**Variables:**  $s$  = states,  $o$  = observations,  $A$  = likelihood mapping between states and outcomes, concentration parameters  $a$  for **A-matrix learning** (perceptual),  $t$  = time point in the trial; when a distinction is made between belief at time  $t$  and belief about a time point  $t$ , the latter is denoted by tau  $\tau$ ;  $D$  = initial state priors,  $B$  = transition matrices denoting state transitions over time, concentration parameters  $b$  for **B-matrix learning** (contingency),  $E$  = matrix of baseline priors over policies,  $C$  = prior over outcomes,  $G$  = **EFE** = Expected free energy, precision  $\gamma$  and its hyperpriors  $\alpha$  (precision in action selection) and  $\beta$  (precision over precision),  $u$  = policies or actions; Arrows denote dependencies between variables, with the variable pointed to conditionally depending on the variable from which the arrow originates.

In **active** inference, both exploratory (information-seeking) and exploitative (reward-seeking) behaviors are explained in terms of **expected free energy (EFE)** minimization. Perception and learning both minimize **variational free energy (VFE)** to optimize posterior beliefs after observing new outcomes [6]. In parallel, action selection and planning selectively sample the environment for observations that minimize EFE. EFE tracks the expected cost minus the expected information gain of an action. This means that decisions that minimize the EFE lead to **reward maximizing** and **uncertainty resolving behavior**.

Inclusion of perceptual learning and contingency learning results in actions guided by the resolution of **epistemic uncertainty** about sensorimotor associations and control.

## RESULTS

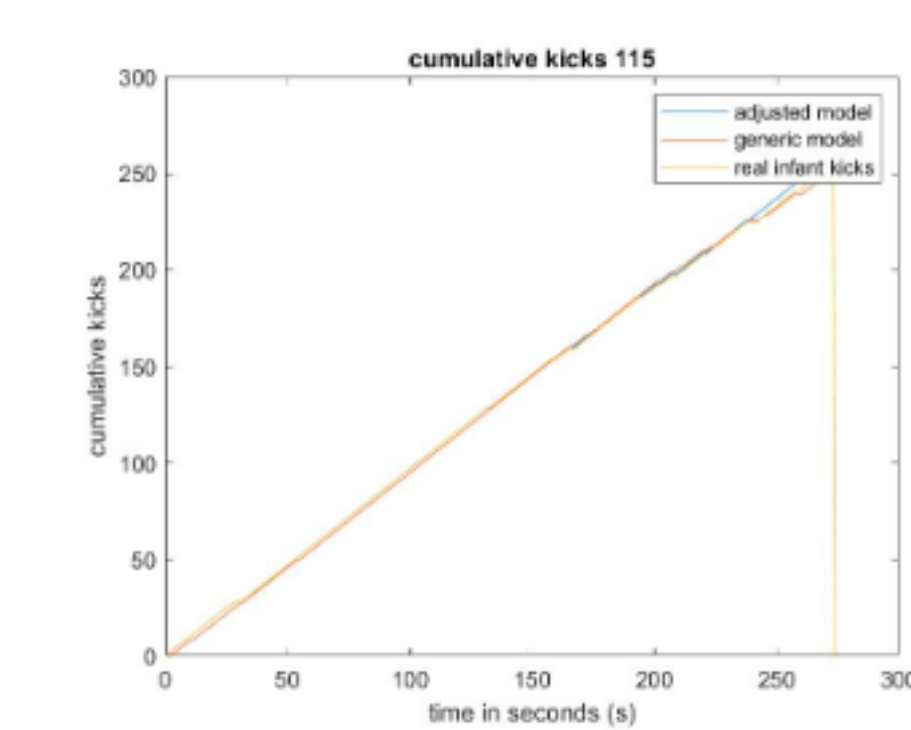
The active inference agent was able to accurately **predict individual infant actions** during the connected phase ( $0.920 < FE < 1.426$ ) based on simulated contingency and perceptual learning during the baseline phases.

**EFE fluctuations indicate that at some points rest actions are more epistemically valuable than kicks.**

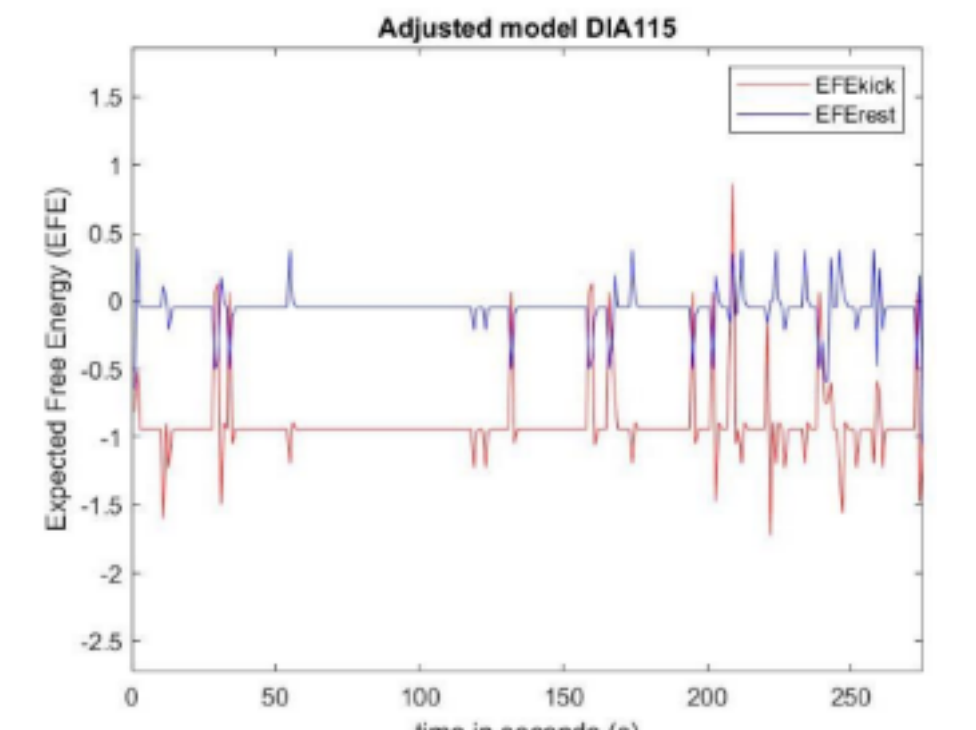
Three infant models with varying baseline kicking activity (low/medium/high) are presented as examples (115, 119 and 120).

## RESULTS

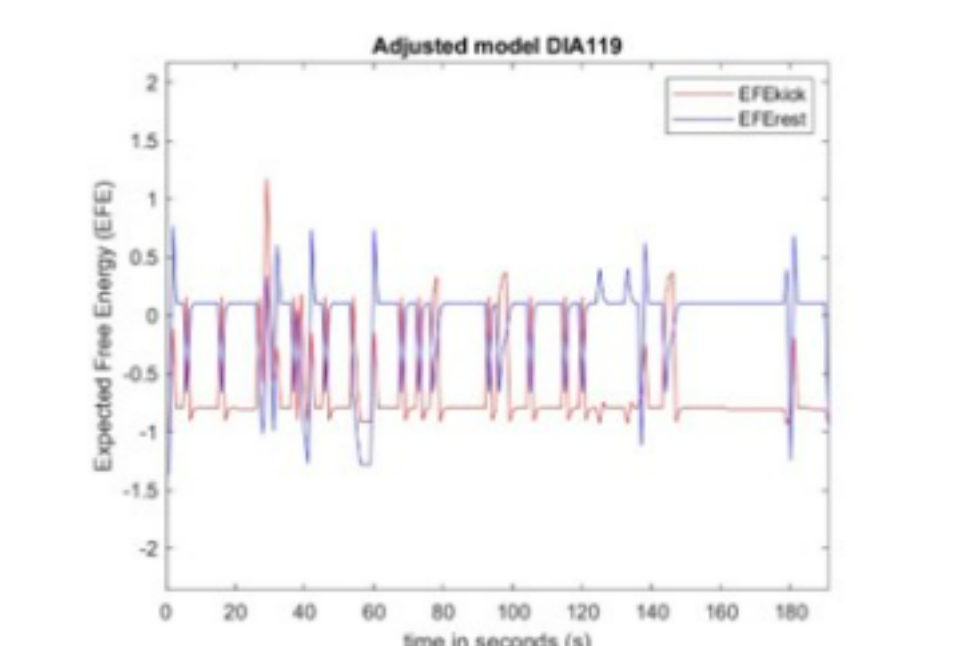
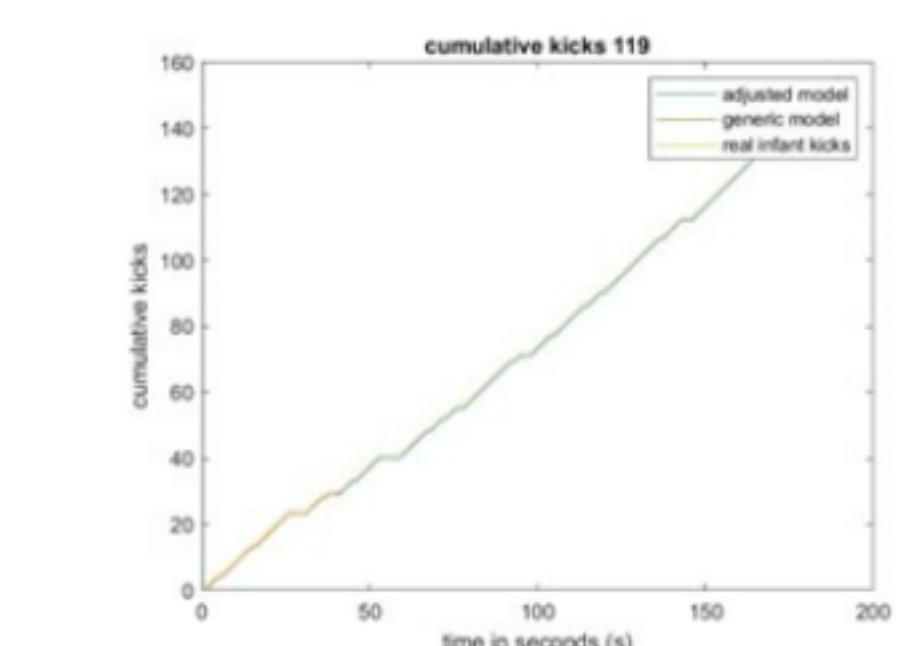
**Cumulative infant kicks (real and predicted) over time:**



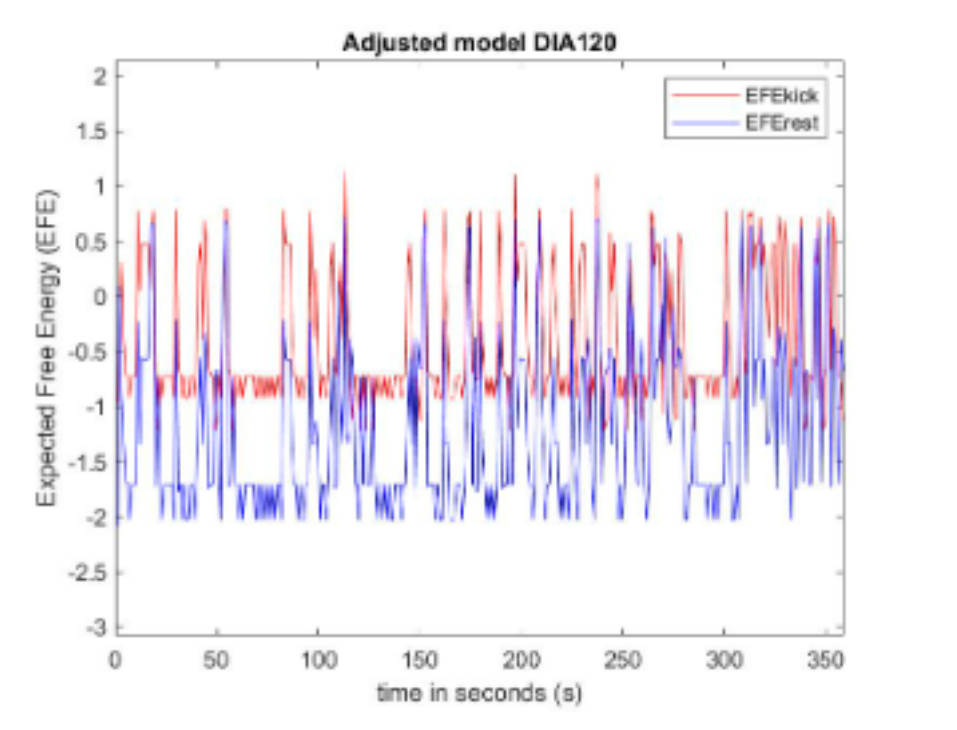
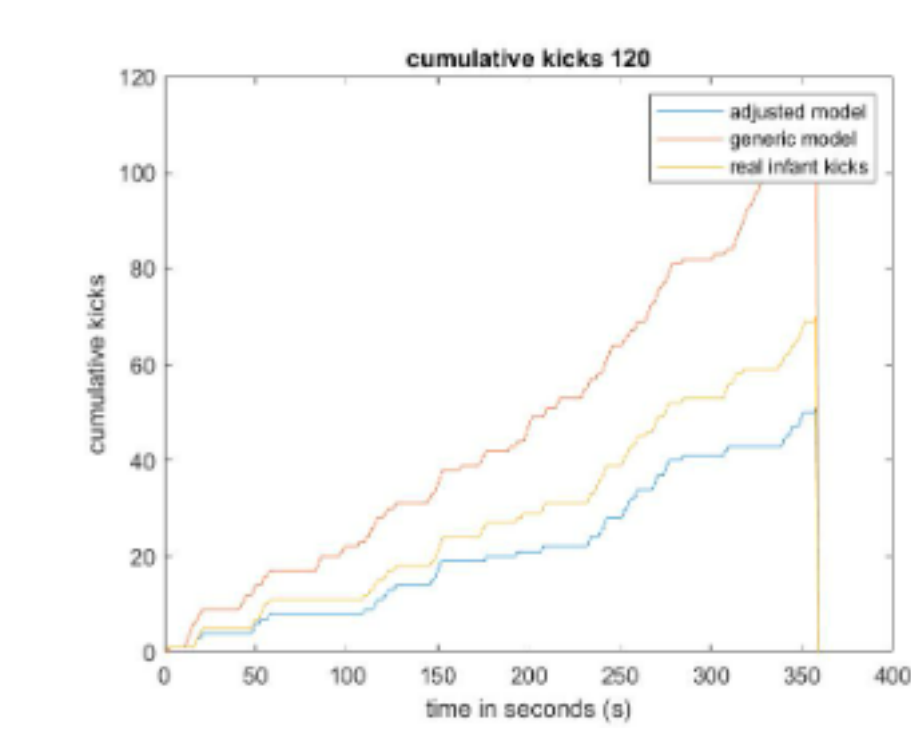
**Expected Free Energy (EFE) for kick and rest actions:**



Infant 115: **high** baseline activity ( $E > 0.6$ )



Infant 119: **medium** baseline activity ( $0.4 \leq E \leq 0.6$ )



Infant 120: **low** baseline activity ( $E < 0.4$ )

The model predicted infant kicks with an average predictive accuracy of 1.2438 (FE).

## CONCLUSION

We formulated an active inference model of infant kicking in MCR and demonstrated its **correspondence to experimental data**.

We included **perceptual** and **contingency learning** to model the **learning of sensorimotor contingencies** associated with the emergence of agency. Contingency learning is a novel active learning mechanism that we added to the spm12 script for active inference modeling.

Our simulations with real infant data show that the model can predict real infant actions in a one-step prediction task, **without assuming explicit rewards**.

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