# Temporal Prediction in Non-Deterministic Continuous Environments: Investigating the Role of Oscillatory Entrainment and Interval Learning

**Elmira Hosseini** (elmira.hosseini@tuebingen.mpg.de)

**Assaf Breska** (assaf.breska@tuebingen.mpg.de)

Max-Planck-Institute for Biological Cybernetics
Tübingen, Germany

## Abstract:

**Interaction with our continuously changing environment relies on anticipating timing of events, enhancing information processing efficiency. Abundant research has investigated temporal prediction in deterministic environments such as isochronous rhythms, where the presumed mechanism is Oscillatory Entrainment (OE) to external rhythms. However, in everyday life, continuous streams lack fully-deterministic temporal regularities. Previous research of temporal prediction in uncertain environments has focused on isolated intervals, suggesting a Distributional-Learning (DL) model. However, in non-deterministic streams, if and under which conditions either of these mechanisms drives prediction is unclear. To address this, we combined computational modeling of the two mechanisms (OE and DL) and human behavioral experiments. We found that while models are affected differently by the degree of variability in the environment, they lead to more overlapping predictions in lower degrees of variability. Next, we used the models generatively to create streams with differential temporal predictions by these two mechanisms, and presented targets at either predicted timepoint to participants conducting a speeded response task. Participants' behavior followed OE predictions in environments with relatively lower degrees of variability to which they were sequentially exposed. Overall, these results highlight the inherent differences between OE and DL mechanisms in dealing with uncertainty, and reveal the flexibility of OE in adapting to partial irregularities, and its independence from DL.**



**Keywords:** Temporal Prediction; Oscillatory Entrainment; Bayesian Updating; Non-deterministic environments; Uncertainty;


# Introduction

The goal of this study is to unravel the computational mechanisms of temporal prediction in continuous non-deterministic streams, in which the inter-stimulus intervals have different levels of variance. For this, we aimed to examine the validity of different computational models (i.e. OE and DL models) by generatively testing their predictions against human behavioral data. OE model is based on synchronization of endogenous brain oscillations to external rhythm by aligning their optimal phase to the rhythmic stimuli (Large and Snyder, 2009). DL models on the other hand have been proposed as a probabilistic representation of the environment by sequential updating when exposed to isolated intervals (Visalli et al., 2019). To control for the hazard effect (Drazin, 1961), we also presented targets that are later than either of the models' predictions.

# Methods

## Computational Modelling and Simulations

We developed and implemented two computational models, Oscillatory Entrainment (Large and Snyder, 2009; Eq. 1) and Conjugate Prior Sequential Bayesian Updating model (Murphy, 2007; Eq. 2), to see how aperiodic streams may lead to temporal prediction of subsequent events and hence proactive preparation.

Eq. 1.

$$\frac{d}{dt}\,\phi = 2\pi F - s(t)c\sin(\phi)$$
$$\frac{d}{dt}\,r = 0$$

Eq. 2.

$$\begin{aligned}
p(\mu,\lambda|D) &= NG(\mu,\lambda|\mu_n,\kappa_n,\alpha_n,\beta_n)\\
\mu_n &= \frac{\kappa_0\mu_0 + n\overline{x}}{\kappa_0+n}\\
\kappa_n &= \kappa_0 + n\\
\alpha_n &= \alpha_0 + n/2\\
\beta_n &= \beta_0 + \tfrac{1}{2}\sum_{i=1}^{n}(x_i-\overline{x})^2 + \frac{\kappa_0 n(\overline{x}-\mu_0)^2}{2(\kappa_0+n)}
\end{aligned}$$

To study the behavior of the models in different levels of stream inter-stimulus interval (ISI) variability, we used a simulation approach. We created a large number of streams with randomly ordered ISIs generated from a normal distribution with specific mean and standard deviation, fed each stream to the two models, and tracked their prediction dynamics. We asked how and under what conditions the predictions of these two mechanisms differentiate.

Finally, used the models antecedently to select streams for behavioral experiments. Therefore, we calculated the predictions of the models on the simulated streams, and selected the streams with the maximum dissociation of predictions of the two models and the desired level of phase coherency of the oscillator model.

## Behavioral Experiment

**Paradigm** Healthy participants participated in two different experiments (n1 = 20, n2 = 25). Participants viewed streams of visual stimuli with different ISI variability: 0% (isochronous), 25% (low jitter), 50% (high jitter). They provided speeded responses to a target presented for a specific stream each time at a different time point which could be the time predicted by the OE model, the DL model, the midpoint between their predictions, or a late target to measure the hazard effect.

# Results

## Simulation Results

For the OE model, we calculated the increase in Inter-Trial Phase Coherency (ITPC) for different shuffles (randomly-ordered ISIs) of the streams in different levels of ISI variabilities. For DL model, we looked into the change in the level of the posterior distribution variance. We found that while the prediction uncertainty of the DL model (posterior variance) is correlated with ISI variability in a strictly positive way, the correlation of prediction uncertainty in OE model (ITPC change) with ISI variability is nonlinear (Fig.1.).

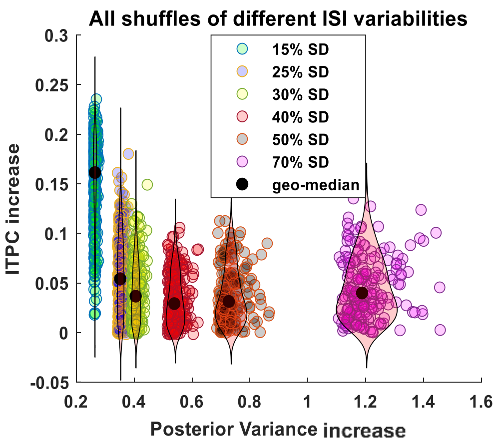


Figure 1. Distribution of all shuffles of ISIs with the same mean (800ms) and different levels of standard deviation based on the amount of ITPC increase in OE model and posterior variance in DL model.

Our simulations also showed that the degree of differentiation of the predictions of the two models depends on the degree of ISI variability (Fig.2.). The lower the jitter the less the models are dissociable.

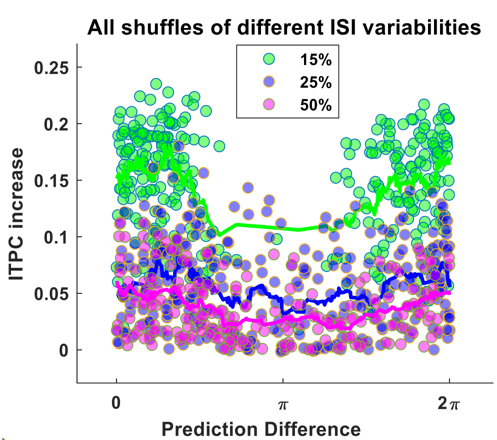


Figure 2. Distribution of all shuffles of ISIs with the same mean (800ms) and different levels of standard deviation based on differentiation of the prediction of the two models and the degree of ITPC increase.

## Behavioral Results

In two different experiments, we presented three types of blocks with different level of ISI variability (0%, 25%,50%). Chosen streams were presented several times within a block, each time followed by a different target position based on the prediction of the models. The two experiments were different in terms of the order of the blocks, and the number of the target positions.

**Experiment 1.** All three blocks were sequentially ordered. The results showed that behavior of the participants follows the prediction of the DL model or hazard function in the jittered environments when there are deterministic environments (i.e. isochronous blocks) interleaved.

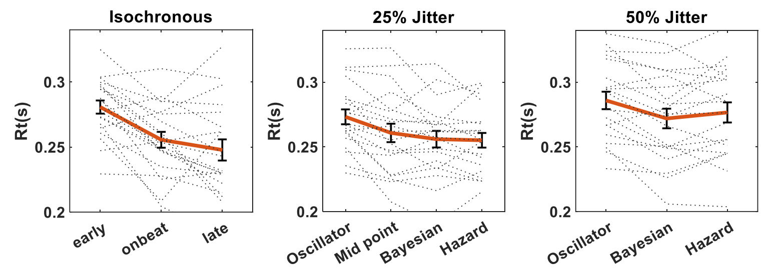


Figure 3. Reaction times of participants for different target positions of all the streams in each block in Experiment 1.

**Experiment 2.** All isochronous blocks were moved to the end. In this experiment we found that participants can use the OE model in environments with lower degrees of uncertainty when they are not exposed to deterministic environments in between.

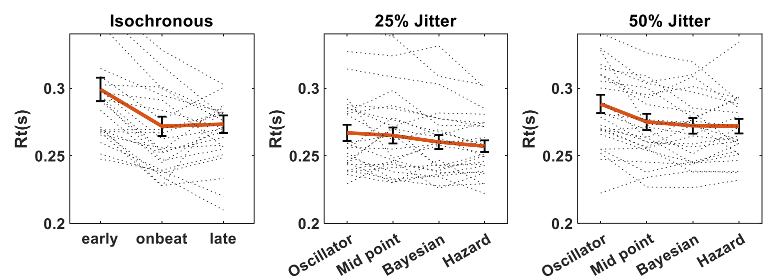


Figure 4. Reaction times of participants for different target positions of all the streams in each block in Experiment 2.

# Discussion

In this study we investigated the computational mechanisms involved in temporal prediction in non-deterministic continuous environments. For this we tested two main models of temporal prediction, OE and DL models, in streams with different levels of ISI variability. Overall, our findings highlight the inherent differences between the two mechanisms in handling uncertainty and further proves that OE can be engaged in non-deterministic contexts with comparably lower variability, while decoupled from Bayesian DL.

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