# Computational Pilot: Optimizing Experimental Design In Temporal Discounting Tasks


Malek Medkour[1] Yanan Liu [2] Paul Masset[3]

1. Honours Cognitive Science. 2. Integrated Program In Neuroscience. 3. Department of Psychology

malek.medkour@mail.mcgill.ca
paul.masset@mcgill.ca

McGill


## Why Optimize Experimental Design in Temporal Discounting?

## MOTIVATION

- **Temporal discounting describes how individuals devalue future rewards and prefer smaller, immediate rewards.**
- **Traditionally studied using animal and human experiments**.
- **Ethical concerns**: Excessive trials, especially in animal research.
- **Inefficiency:** Fixed trial numbers may not optimize parameter recovery.

## APPROACH

- **A Computational Pilot simulates real behaviour** and optimizes task design before data collection, addressing ethical concerns by minimizing unnecessary trials.
- **Improves efficiency** by refining task parameters, minimizing resource waste.
- **Enhances model accuracy** by identifying the best task structure for robust parameter recovery.

## How Has Temporal Discounting Been Studied?

- Debate whether discounting is constant (exponential) or initially steep, then slowing over time (hyperbolic). (See ***Fig. 1***)
- Studies show that animals and humans often prefer smaller, immediate rewards over larger, delayed rewards, consistent with hyperbolic discounting.
- Kobayashi et al. (2008) studied this effect in primates using an intertemporal choice task. (See ***Fig. 2A***)

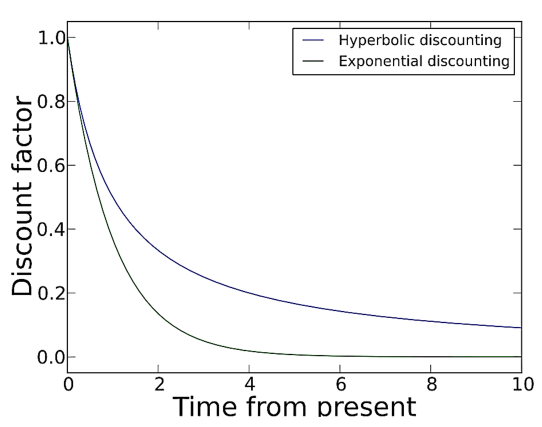


***Fig. 1: Hyperbolic VS Exponential discounting rate.***

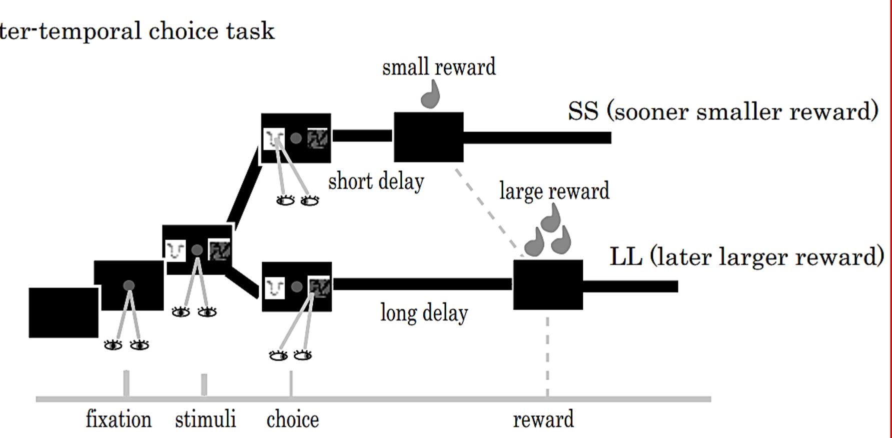


***Fig. 2A: Intertemporal Choice Task Design from Kobayashu et al. (2008).*** Animals choose between a smaller, immediate reward (SS) and a larger, delayed reward (LL). By varying the delay, we measure how future rewards lose subjective value over time.

## What Did Kobayashi et al. Find?

- Kobayashi et al. (2008) fit observed choice behavior using a Weibull function to model SS choices as a function of SS reward.
- They extracted indifference points where $P(SS)$=50% and used them to estimate $k$ by fitting a hyperbolic model to discounting behavior.
- Their findings confirmed that hyperbolic discounting better explains choices compared to exponential models.

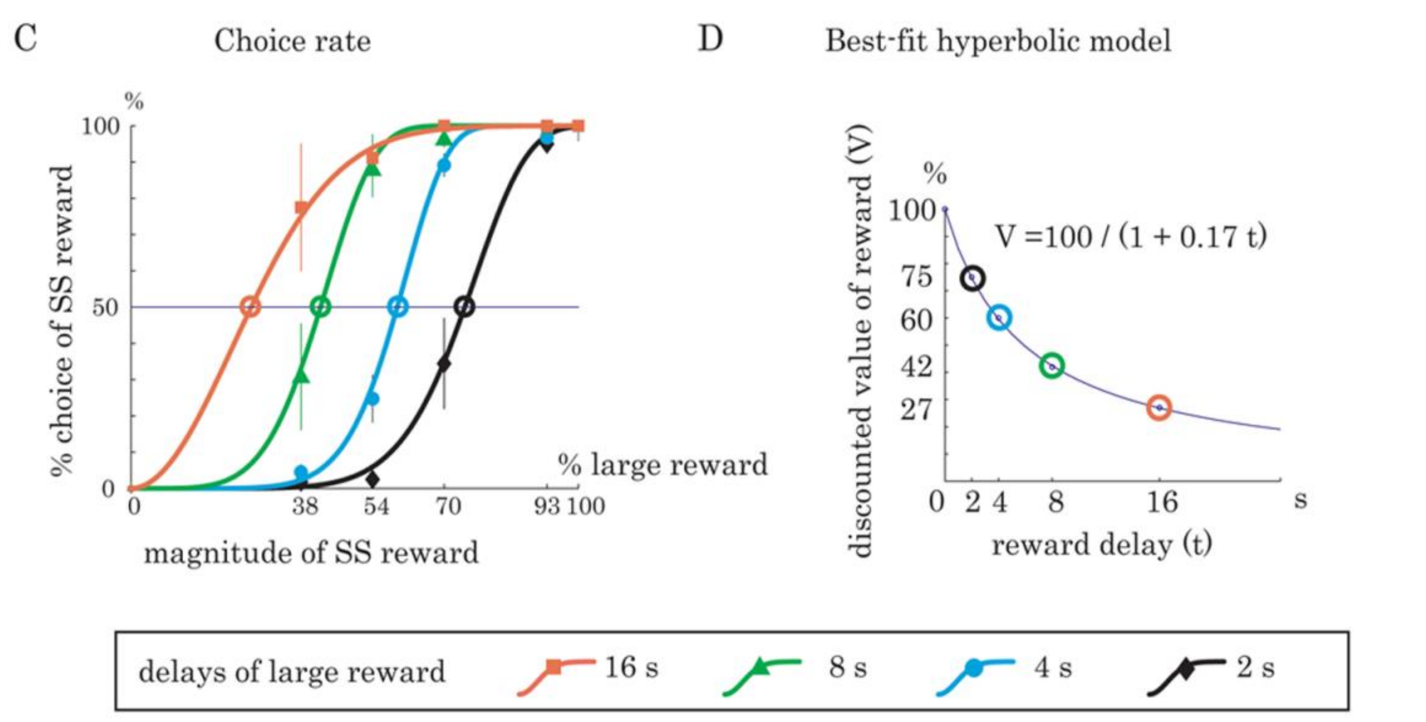


***Figure 2C/2D:*** *A Weibull function was used to fit observed choices, and a hyperbolic model was then applied to estimate $k$ from extracted indifference points*

## Is There An Issue? What Is Missing?

- **Kobayashi et al. used a fixed number of trials and reward delays**, which may have affected model accuracy.
- **Their use of the Weibull function assumes it is the best-fitting psychometric model**, but alternative models (e.g., Logistic, Gompertz) might better capture choice behavior.
- **Different psychometric models could improve $k$ recovery**, leading to more precise discounting estimates.
- **A Computational Pilot could test multiple models** and task designs to optimize parameter recovery before real data collection.

## Our solution: A Computational Pilot

- We introduce a Computational Pilot to optimize task structure before data collection.
- By coding and simulating decision-making agents, we can refine the psychometric curve choice and fine-tune trial numbers and reward delays to improve parameter recovery.
- This allows us to reduce inefficiencies, increase statistical power, and enhance model selection for temporal discounting studies.

## STEP 1 - Simulate Temporal Discounting Behavior From Virtual Agent

### *1) Temporal Discounting Value Calculation*

$$V_{SS} = \frac{\text{SS Reward}}{1 + k \cdot \text{SS Delay}} \qquad V_{LL} = \frac{\text{LL Reward}}{1 + k \cdot \text{LL Delay}}$$

- Rewards are discounted over time using a hyperbolic function. We obtain a calculated subjective values ($VSS$, $VLL$) of Sooner Smaller and Later Larger rewards, depending on the delay of LL (2s, 6s ,8s or 16s).

### *2) Probabilistic Decision-Making : Softmax Rule*

- $\lambda$ = Sensitivity parameter (inverse temperature), controlling decision stochasticity.
- P(SS) = Probability of selecting the smaller, sooner (SS) reward
- $e$ = Exponential base

$$P(SS) = \frac{e^{-\lambda V_{SS}}}{e^{-\lambda V_{SS}} + e^{-\lambda V_{LL}}}$$

### *3) Stochastic Choice : Bernoulli Process*

- Stochasticity is introduced to simulate variability in real decision-making via a uniform random variable r.
- The choice follows a Bernoulli process, comparing $P(SS)$ with $r$

$$\text{Choice} = \begin{cases} 1, & P(SS) \geq r \\ 0, & P(SS) < r \end{cases} \quad r \sim U(0,1)$$

## STEP 2 - Fit Psychometric Curves & Estimate Discounting Rate $k$

- We fit three psychometric models (Weibull, Gompertz, Logistic), to observed choice data to model how SS choices change with SS reward.
- These ***(Fig. 3 A, B, C)*** are an example of 3 psychometric model fits and recovered indifferent points from1 simulated trial.

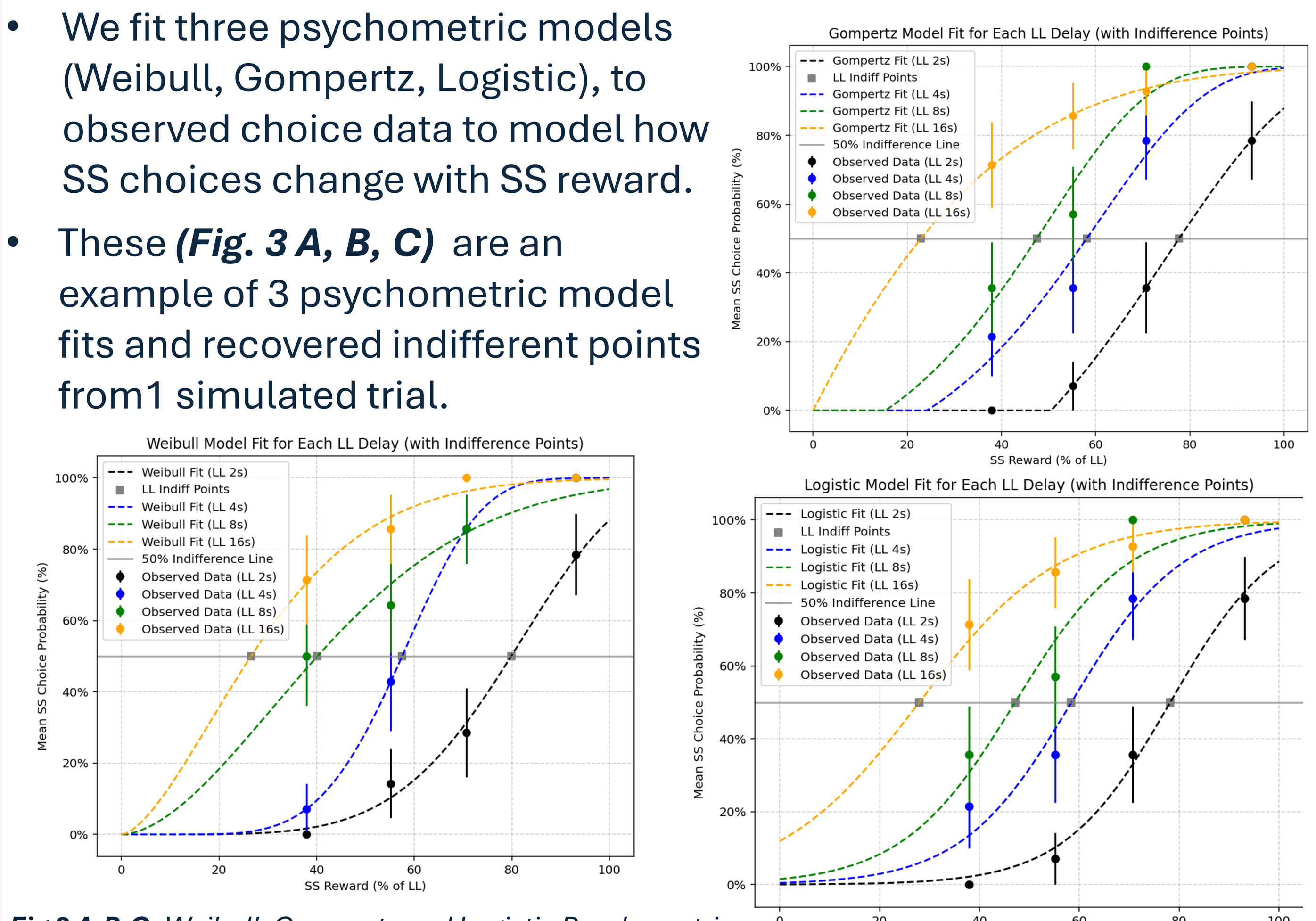


*Fig 3 A,B,C: Weibull, Gompertz and Logistic Psychometric Model fits for SS choice behavior with indifference points.*

- A hyperbolic function was used to estimate the discounting rate $k$ from the indifference points of the 3 models.

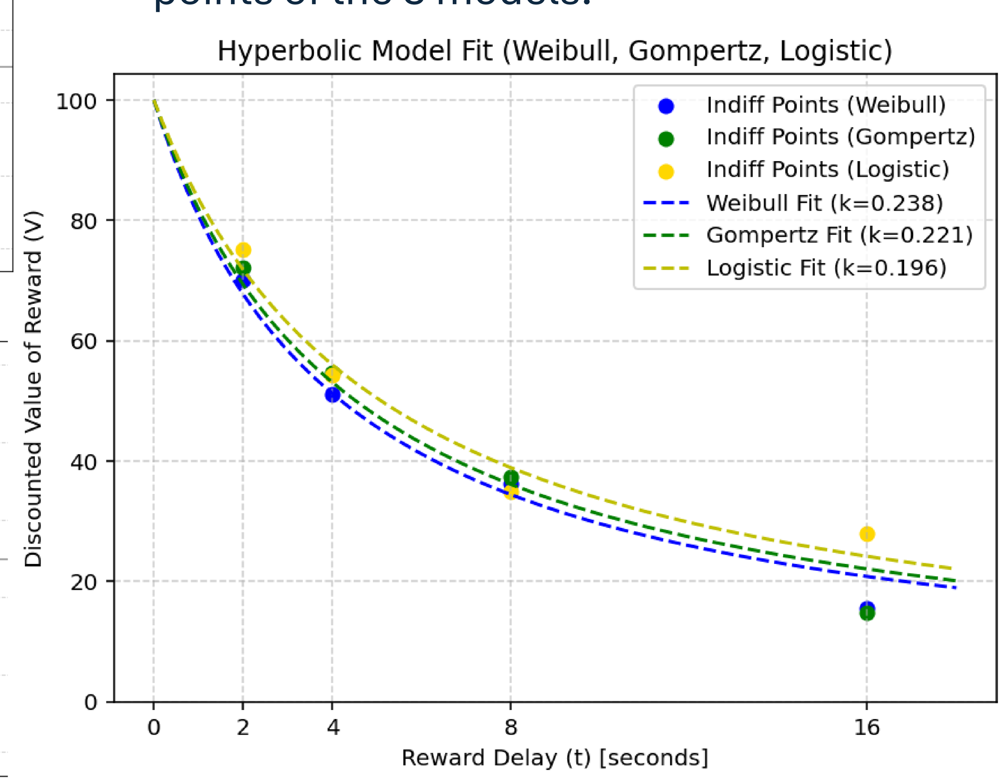


***Fig. 4:*** *A Hyperbolic Model Fit compares the recovered k from the 3 functions in a single trial. True k was 0.17.*

## STEP 3: Evaluate Model Accuracy & $k$ Recovery

- With a Computational Pilot, we were able to compare $k$ recovery across 100 simulated trials with the 3 different psychometric models.
- We performed a T-Test on all models. The Logistic model (yellow) produced the most accurate and stable $k$ estimates, closely aligning with the true $k$. Weibull & Gompertz showed greater variability in $k$ recovery.

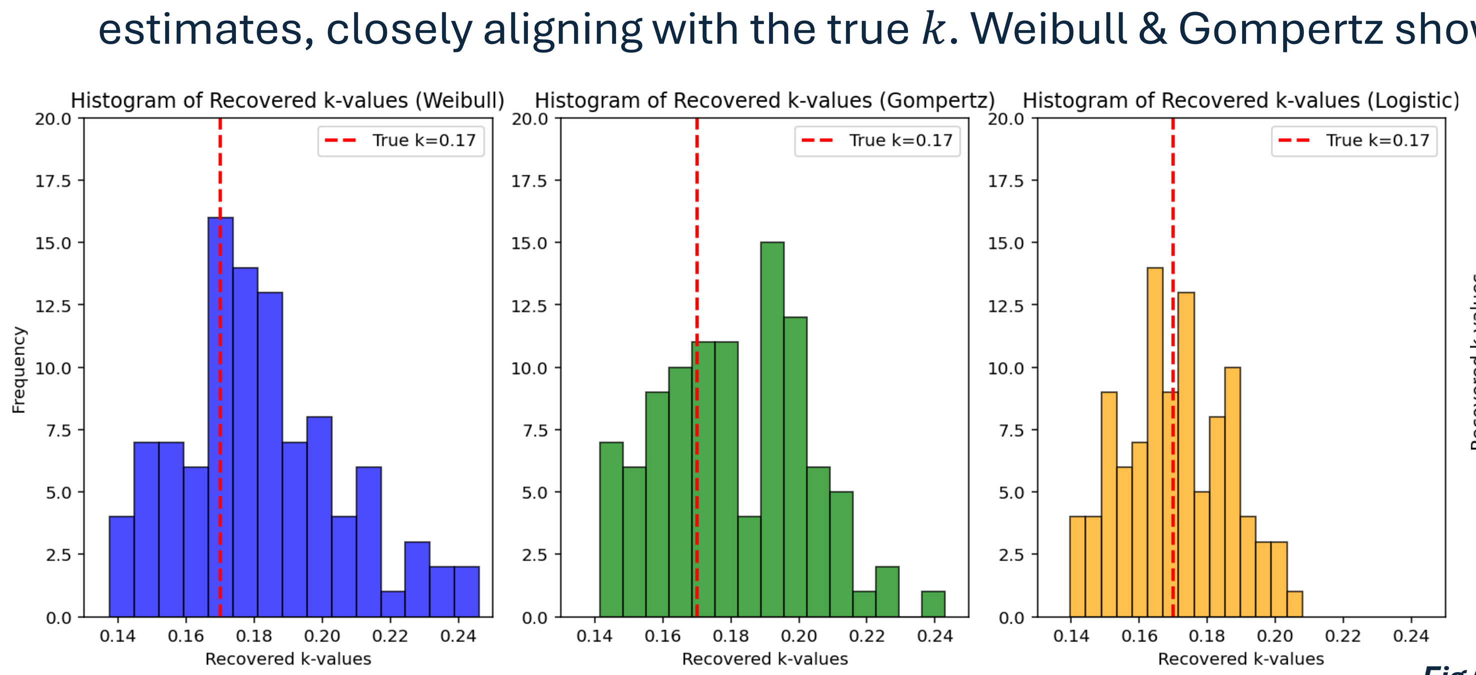


***Fig.5 A ,B, C:*** *Histograms show recovered $k$ values from 100 trials across 3 different models.*

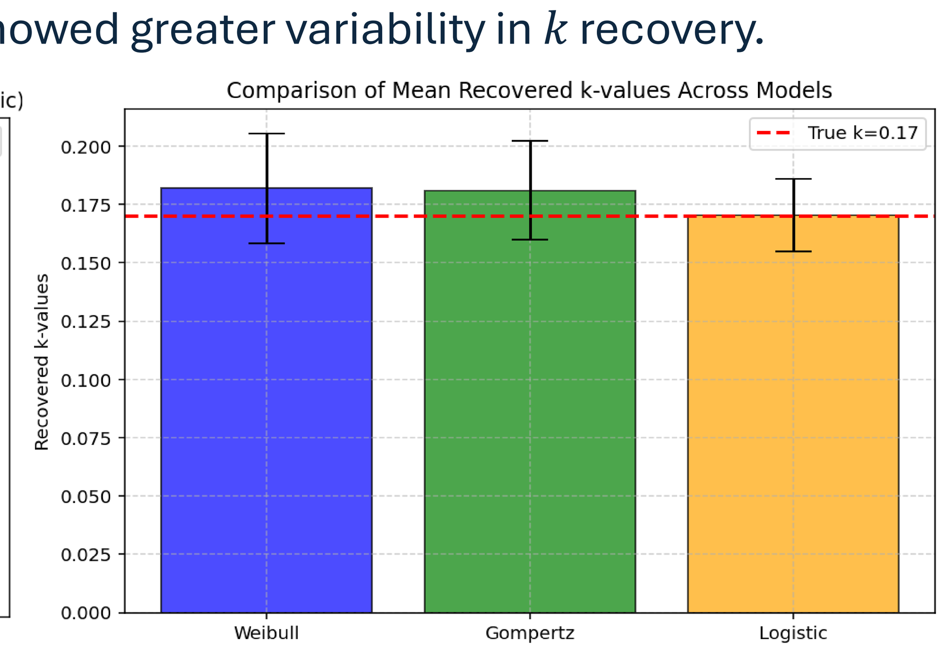


***Fig 6.*** *T-Test of the models. The bar plot compares mean recovered $k$, showing logistic fits yield the most accurate estimates.*

## STEP 4 & Future Work: Optimize Task Design Through Power Analysis

- **Conduct power analysis to determine optimal trial numbers and reward delays.**
- **Assess how task configurations(trial numbers and reward delays influence parameter recovery ($k$) and model fit. Refine task design to enhance statistical power and improve parameter estimation.**

## References


1. Kobayashi, S., & Schultz, W. (2008). Influence of reward delays on responses of dopamine neurons. *Journal of Neuroscience, 28*(31), 7837–7846.
2. Robert C Wilson, Anne GE Collins (2019) Ten simple rules for the computational modeling of behavioral data eLife 8:e49547.


## Acknowledgements


HEALTHY BRAINS HEALTHY LIVES

CANADA FIRST RESEARCH EXCELLENCE FUND

APOGÉE CANADA FONDS D'EXCELLENCE EN RECHERCHE