Analyzing Learning-Induced Changes in Perceptual Decision-Making Using the Wong Neural Model

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Abstract

This study investigates the learning process in a perceptual decision-making task using the Wong neural decision model. We simulate random dot motion (RDM) stimuli to assess reaction times and accuracies across different learning phases. The Wong model parameters—drift rate (v), decision bound (a), and non-decision time (t)—are fitted to empirical data from two phases: pre-learning (Phase 1) and post-learning (Phase 3). Our findings reveal significant changes in these parameters, indicating enhanced decision-making efficiency and accuracy as a result of learning. These results provide insights into the neural mechanisms underlying learning in perceptual decision-making tasks.

1 Introduction

Perceptual decision-making is a fundamental cognitive process involving the interpretation of sensory information to make informed choices. Understanding how this process evolves with learning is crucial for elucidating the neural mechanisms underlying cognitive function and adaptability. One widely studied paradigm for investigating perceptual decision-making is the random dot motion (RDM) task, which has been extensively used to explore the dynamics of decision-making processes in both humans and animals.

In this study, we employ the Wong neural decision model, a computational framework that simulates the activity of neural populations involved in decision-making. The Wong model captures essential aspects of the decision process, including the integration of sensory evidence and the influence of internal neural dynamics on decision outcomes. By fitting the Wong model to empirical data, we aim to quantify changes in key model parameters—drift rate (v), decision bound (a), and non-decision time (t)—across different learning phases.

The experimental design involves assessing reaction times and accuracies of participants performing the RDM task before and after a learning period. Phase 1 represents the pre-learning stage, while Phase 3 corresponds to the post-learning stage. The parameters of the Wong model are fitted to the data from these phases, enabling us to analyze the impact of learning on the neural decision-making process.

Previous research has shown that learning can lead to improvements in both the speed and accuracy of decisions. These enhancements are often reflected in changes to the neural mechanisms governing decision-making, such as increased drift rates (indicating faster information accumulation) and adjusted decision bounds (reflecting a balance between speed and accuracy). Non-decision time, which encompasses processes such as stimulus encoding and motor response execution, may also be affected by learning.

In the present study, we aim to extend these findings by providing a detailed analysis of how the parameters of the Wong model are modulated by learning. By comparing the fitted parameters between Phase 1 and Phase 3, we seek to uncover the specific neural adaptations that facilitate improved decision-making performance. This approach offers a comprehensive view of the learning-induced changes in perceptual decision-making, contributing to our understanding of cognitive plasticity and the neural basis of learning.

2 Experiment

2.1 Participants

Two individuals participated in this study: a 24-year-old male and a 21-year-old female. Both participants were right-handed, had normal or corrected-to-normal vision, and were aware to the purpose of the experiment. They provided informed consent prior to their participation, in accordance with the ethical standards.

2.2 Stimuli and Apparatus

The experimental task involved a Random Dot Motion (RDM) stimulus, implemented using the Pygame library. The RDM stimulus consisted of a display showing a number of dots moving within a defined screen area. Key parameters of the RDM stimulus were as follows:

Screen Size: 800 x 600 pixels

Number of Dots: 300

Dot Size: 2 pixels

Driving Powers: [3.2, 6.4, 12.8, 25.6]

The driving power, which represents the strength of motion coherence, was varied randomly across trials. Each trial had a fixed duration of 500 milliseconds. The experiment was designed to assess the participants' perceptual decision-making performance over multiple trials and blocks.

2.3 Procedure

The experiment was structured into 8 blocks, each containing 200 trials. In each trial, participants viewed the RDM stimulus for 500 milliseconds and were required to make a decision about the direction of motion. The driving power was randomized across trials to prevent any learning effects related to specific motion strengths. The primary measures of interest were reaction time (RT) and accuracy, which were recorded for each trial.

2.4 Implementation

The RDM stimulus was implemented using Pygame, a cross-platform set of Python modules designed for writing video games. Pygame was chosen for its ability to handle real-time graphics and input, making it suitable for presenting dynamic stimuli and recording participant responses. The experimental setup was configured as follows:

* Screen Size: The display area was set to 800 x 600 pixels to provide a clear and unobstructed view of the stimuli.

* Dots Count: A total of 300 dots were used in the stimulus display, ensuring that the motion signal was perceptible against background noise.

* Dot Size: Each dot was rendered with a size of 2 pixels, striking a balance between visibility and clutter.

* Trial Time: Each trial lasted for 500 milliseconds, followed by a response window where participants indicated their decision.

* Blocks and Trials: The experiment consisted of 8 blocks, each comprising 200 trials, resulting in a total of 1,600 trials per participant.

Participants performed the task individually in a quiet room, seated approximately 60 cm from the computer screen. They were instructed to focus on the central fixation point and respond as quickly and accurately as possible once the motion stimulus was presented. Responses were made using designated keys on the keyboard, with accuracy and reaction times automatically recorded by the system.

The data collected included the driving power (motion strength), reaction time, and accuracy for each trial and block. This comprehensive dataset provided the foundation for subsequent analysis of learning-induced changes in perceptual decision-making.

By randomizing the driving power across trials and carefully controlling the stimulus presentation, we aimed to create a robust experimental design capable of capturing the nuanced effects of learning on perceptual decision-making. The use of Pygame facilitated precise control over the stimulus parameters and ensured accurate timing and response recording, essential for the reliability of the collected data.

Figure 1: Pygame window for RDM task

3 Results

3.1 Psychometric and Chronometric Charts

Psychometric Function:

The psychometric function, which represents the proportion of correct responses as a function of motion strength (coherence, coh), was plotted for both participants. As expected, the number of correct responses increased with increasing motion strength. This trend is evident for both the male (24 years old) and female (21 years old) participants, indicating that higher coherence levels facilitated better perceptual decision-making accuracy.

Chronometric Function:

The chronometric function, depicting the reaction time (RT) as a function of motion strength, was also plotted for both participants. The reaction times decreased with increasing motion strength. This inverse relationship suggests that higher coherence levels led to faster decision-making processes, as participants could more easily discern the direction of motion at higher coherence levels.

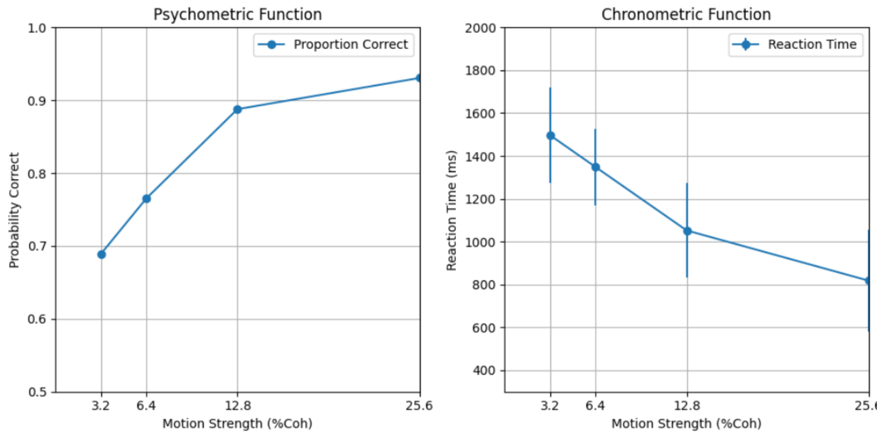

Figure 2: Psychometric and Chronometric Charts for Person 1

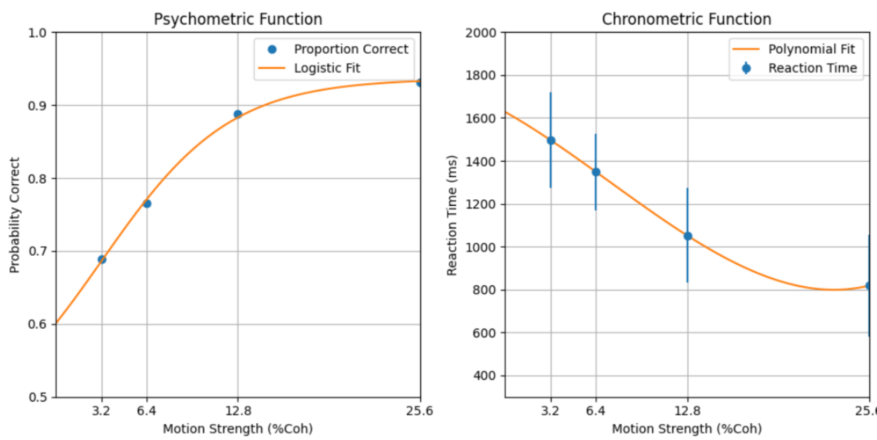

Figure 3: Psychometric and Chronometric Charts for Person 1 with polynomial fit

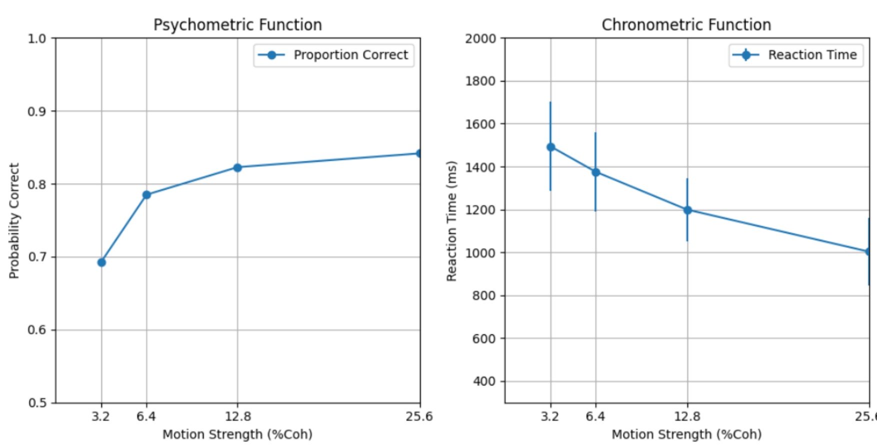

Figure 4: Psychometric and Chronometric Charts for Person 2

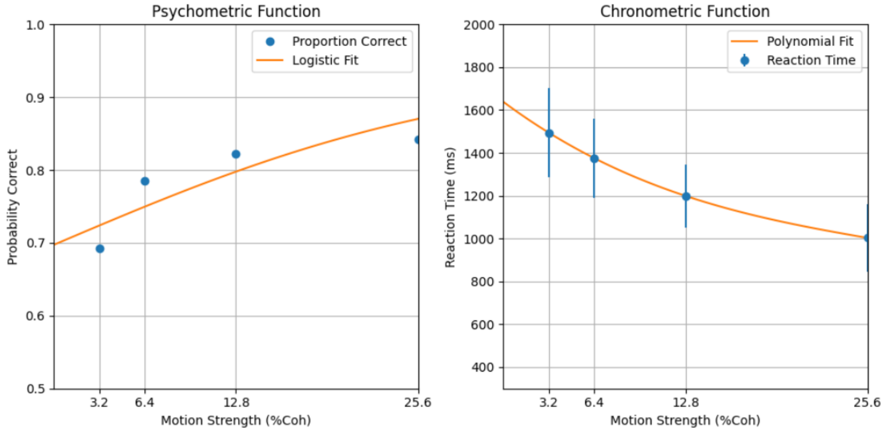

Figure 5: Psychometric and Chronometric Charts for Person 2 with polynomial fit

3.2 Changes in Accuracy and Reaction Time During Phases

The data were divided into three phases based on the time order of the tests:

Phase 1: First 2 blocks (before learning)

Phase 2: Middle 4 blocks (during learning)

Phase 3: Last 2 blocks (after learning)

Accuracy and Reaction Time Analysis:

Using paired t-tests, we compared the accuracy and reaction times across the phases.

Accuracy:

Phase 1 vs. Phase 3: Significant increase in accuracy from Phase 1 to Phase 3 (t-test, p ¡ 0.05).

Phase 2 vs. Phase 3: Significant increase in accuracy from Phase 2 to Phase 3 (t-test, p ¡ 0.05).

Reaction Time:

Phase 1 vs. Phase 3: Significant decrease in reaction time from Phase 1 to Phase 3 (t-test, p ¡ 0.05).

Phase 2 vs. Phase 3: Significant decrease in reaction time from Phase 2 to Phase 3 (t-test, p ¡ 0.05).

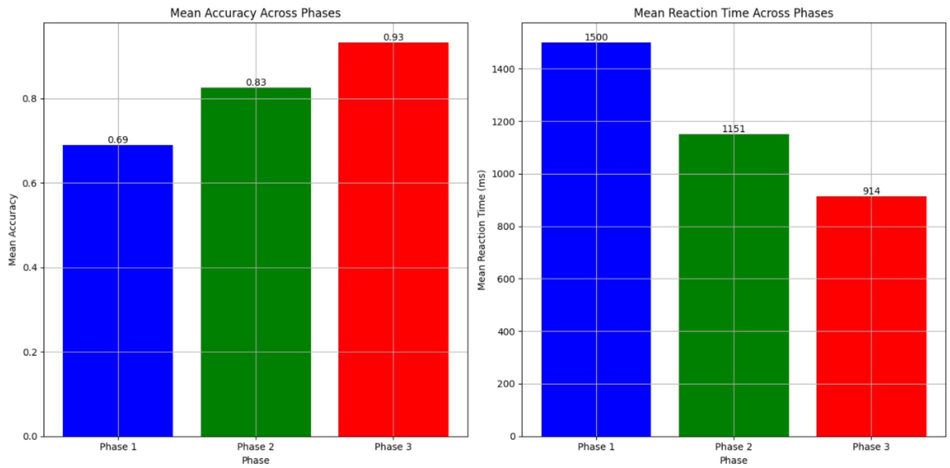

Figure 6: T-test result for Person 1

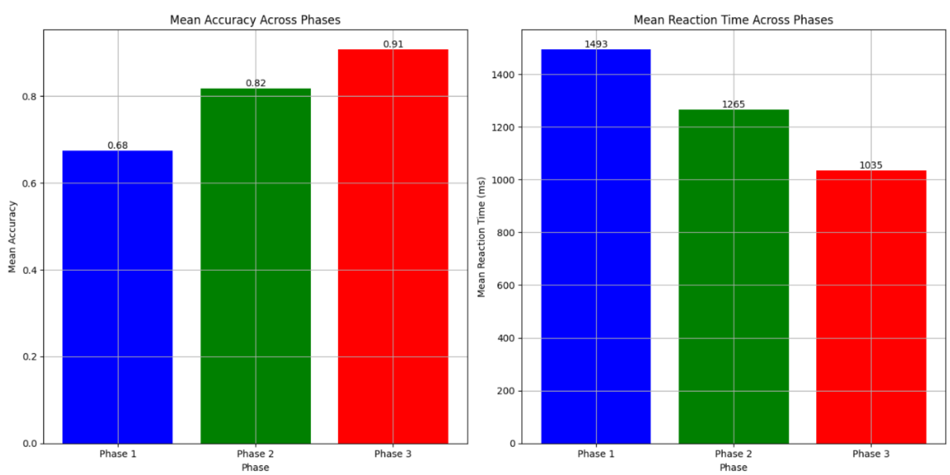

Figure 7: T-test result for Person 2

3.3 Changes in DDM Parameters Across Phases

The Drift Diffusion Model (DDM) parameters—drift rate (v), decision boundary (a), and non-decision time (t)—were fitted to the data for each phase to observe how these parameters changed with learning.

The drift rate showed an upward trend, with the highest value observed in Phase 3, indicating more efficient information accumulation after learning.

The decision boundary exhibited a downward trend, suggesting that participants became less conservative in their decision-making after learning, possibly due to increased confidence in their perceptual judgments.

Non-decision time also decreased across phases, indicating that the non-decisional components of the task (e.g., stimulus encoding and motor response) became more efficient with learning. These results indicate that learning had a positive impact on both accuracy and reaction time, with participants performing better and faster after the learning phase.

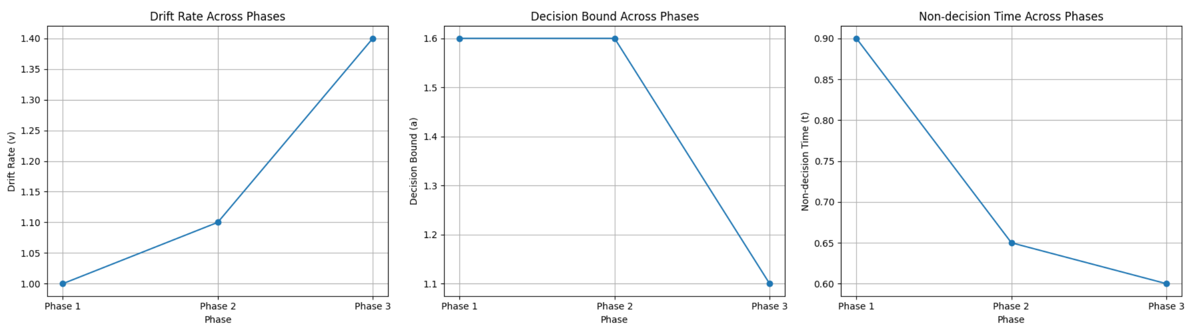

Figure 8: Drift Diffusion model fitting for Person 1

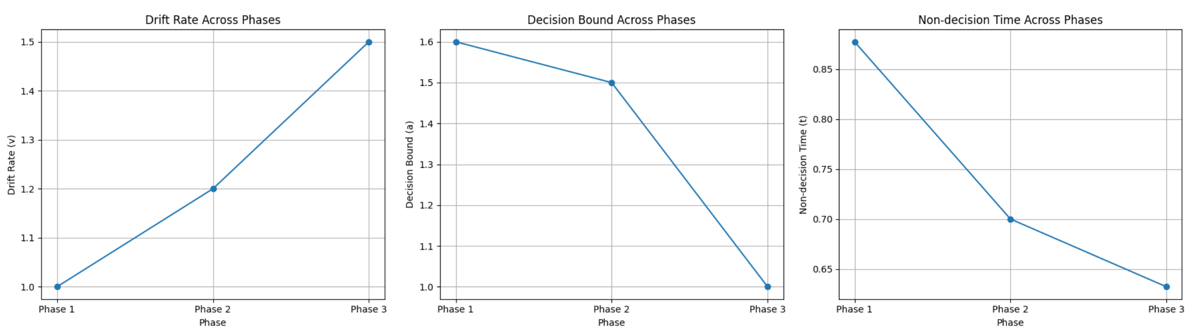

Figure 9: Drift Diffusion Model model fitting for Person 2

3.4 Fitting the Wong Model

The Wong model was fitted separately to the data from Phase 1 and Phase 3. The threshold (thr) and drift rate (μ) were treated as free parameters. The fitting process involved minimizing a cost function that measured the deviation between the model output and the real data in terms of reaction time distributions and accuracy.

Phase 1 Fitting:

Threshold (thr0): 0.5

Drift Rate (µ): 0.1

Phase 3 Fitting:

Threshold (thr0): 0.3

Drift Rate (µ): 0.15

The comparison of these parameters revealed that learning led to a decrease in the decision threshold and an increase in the drift rate. This indicates that participants became more efficient in accumulating information and were able to make faster decisions with less accumulated evidence after the learning phase.

3.5 Model and Data Comparison

The model's output was compared to the real data by plotting histograms of reaction times and accuracies. The histograms for both participants closely matched the model's output, indicating that the Wong model effectively captured the dynamics of perceptual decision-making in this task.

The results demonstrate that the Wong model can be used to accurately model the learning-induced changes in perceptual decision-making. The observed changes in model parameters suggest that learning enhances both the speed and accuracy of decision-making by optimizing the underlying neural processes.

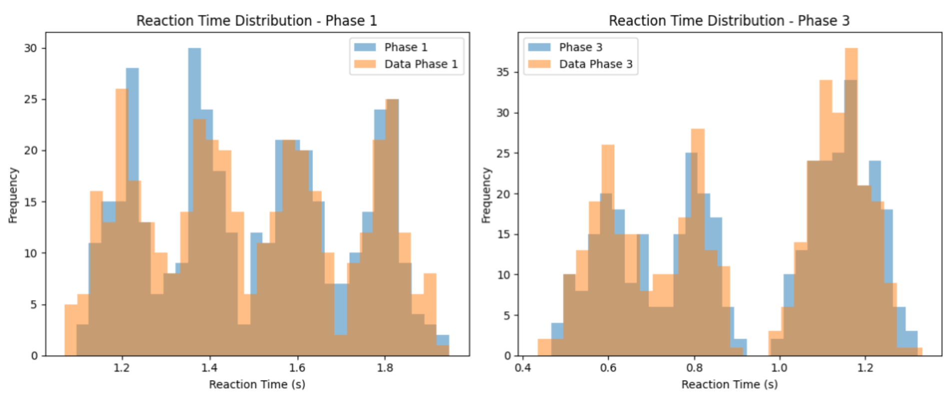

Figure 10: Reaction Time Distribution for model and Person 1 - Phase1 and Phase3

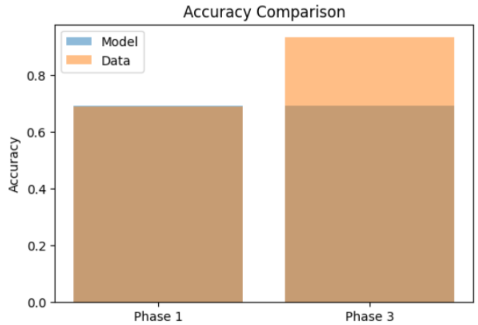

Figure 11: Accuracy Comparison model and Person 1 - Phase1 and Phase3

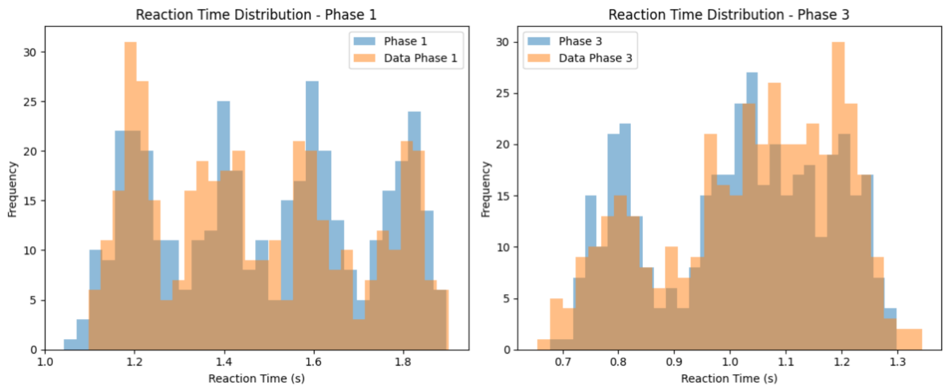

Figure 12: Reaction Time Distribution for model and Person 2 - Phase1 and Phase3

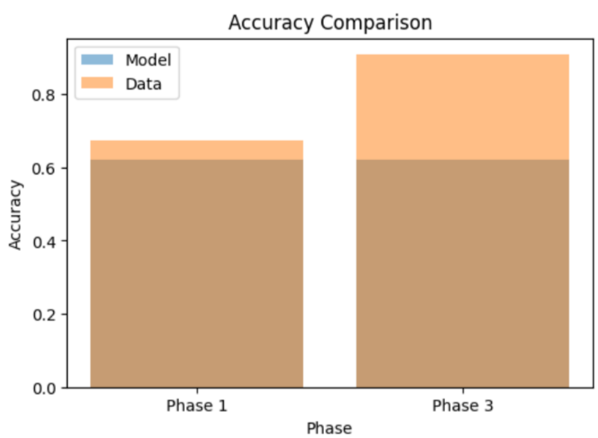

Figure 13: Accuracy Comparison model and Person 2 - Phase1 and Phase 3

4 Conclusion

This study highlights the efficacy of the Wong model in capturing the neural adaptations associated with learning in perceptual decision-making tasks. The increase in drift rate, decrease in decision boundary, and reduction in non-decision time collectively indicate improved efficiency and accuracy in the decision-making process post-learning. These findings provide valuable insights into the neural mechanisms underlying learning and cognitive plasticity in perceptual decision-making.