A study of the learning process in a perceptual decision-making activity

Parsa Palizian
Prof.Reza Ebrahimpour
parsapalizian81@gemailcom

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Abstract

In this study, we explored the learning process in a perceptual decision-making task using a Random Dot Motion (RDM) paradigm over different phases. We utilized the Drift Diffusion Model (DDM) to examine the dynamics of decision-making by assessing changes in the drift rate, decision boundary, and non-decision time. Our findings reveal a distinct pattern of improved decision-making efficiency as participants advanced through the experiment. Specifically, we noted an increase in drift rate and a decrease in both decision boundary and non-decision time, suggesting enhanced processing speed and reduced caution with time. These results not only support the usefulness of the DDM in analyzing the components of decision making but also underscore the influence of learning and adaptation on perceptual decision-making tasks.

1 Introduction

Decision making is a fundamental cognitive process that enables individuals to choose between different courses of action based on available information. It is a complex phenomenon that involves the integration of perceptual evidence, memory, and strategic considerations. Understanding the underlying mechanisms of decision making is crucial for unraveling how humans and animals adapt to their environments and make choices that maximize their survival and success.

Two prominent models have been developed to explain the dynamics of decision making: the Drift Diffusion Model (DDM) and the Wang Model. Both models offer valuable insights into how decisions are made, but they do so from different perspectives and with distinct assumptions.

The Drift Diffusion Model (DDM) is a widely used mathematical model that describes the decision-making process as a noisy accumulation of evidence towards one of two choice options. According to the DDM, decision making involves several key components: the drift rate, which represents the speed of evidence accumulation; the decision boundary, which determines the amount of evidence needed to make a decision; and the non-decision time, which accounts for the sensory and motor processes that are not directly related to the decision itself. The DDM has been particularly successful in explaining reaction time distributions and accuracy rates in simple two-choice tasks, making it a cornerstone of decision-making research.

On the other hand, the Wang Model offers a neurobiological perspective on decision making. It is based on the dynamics of recurrent neural networks and emphasizes the role of neural activity in the prefrontal cortex and other brain areas involved in decision making. The Wang Model incorporates the idea of attractor dynamics, where the brain's neural network settles into stable states corresponding to different decision outcomes. This model provides a mechanistic understanding of how neural circuits can integrate information over time and reach a decision, highlighting the importance of synaptic connectivity and neural plasticity in shaping decision-making processes.

In this paper, we aim to investigate the learning process in a perceptual decision-making task using a Random Dot Motion (RDM) paradigm. We will employ the Drift Diffusion Model (DDM) to analyze the changes in decision-making dynamics across different phases of the experiment. Additionally, we will consider the implications of our findings in the context of the Wang Model, exploring how neural mechanisms might underpin the observed behavioral changes.

By combining insights from both the DDM and Wang Model, we hope to provide a comprehensive understanding of the factors that influence decision-making efficiency and the role of learning and adaptation in perceptual decision-making tasks. Our study aims to bridge the gap between mathematical modeling and neurobiological mechanisms, offering a holistic view of decision-making processes.

2 Methodology

Two participants (both female; both right-handed; aged between 31 and 47 years) performed our RDM task. All the participants had a normal or corrected to-normal vision, and none of them had any history of psychiatric and neurological diagnosis.

In our experiment, participants were tasked with indicating the predominant direction of motion (left or right) in a cloud of moving dots. They were seated in an adjustable chair in a semi-dark room, with their chin and forehead supported, facing a display monitor (15.6-inch; refresh rate, 144 Hz; screen resolution, 2560 x 1440; viewing distance, 50 cm).

During the Random Dot Motion (RDM) task, each trial began with a red fixation point appearing at the center of the display. After participants fixated on the point and pressed the space bar, two choice targets appeared on the left and right sides of the screen, corresponding to the possible motion directions. Participants indicated their responses by pressing the left or right key as soon as they determined the direction of motion. Both the direction and strength of the motion varied randomly from trial to trial. Motion coherence levels were chosen from the following six values: 0

Subjects completed a session consisting of eight blocks, with each block containing 204 trials. The coherence levels were randomly selected for each trial. The experiment was presented using code written in PsychToolbox.

Participants were required to respond within five seconds, and received distinctive auditory feedback (beep tones) for correct and incorrect responses. Reaction time (RT) was measured from the onset of the motion stimulus to the moment the left or right key was pressed.

A total of 3264 trials were collected from 16 experimental blocks. The probability of correct responses and the reaction times (RT) against motion strength were calculated and plotted.

The experiment was divided into three phases: Phase 1 consisted of the first two blocks, Phase 2 included the next four blocks, and Phase 3 comprised the final two blocks.

To verify our behavioral data, the RT and accuracy data were fitted to a drift diffusion model. We used the fast-dm toolbox for the fitting procedure, employing Kolmogorov-Smirnov (KS).

We evaluated the variation in drift rate, boundary separation, and non-decision time across all phases and subjects. The absolute values of all parameters were reported, with non-decision time represented in seconds.

3 Results

Two subjects performed a Random Dot Motion (RDM) task where they simultaneously reported the perceived direction of the moving dots. Given that evidence strength is known to correlate with accuracy and decision time we anticipated observing higher accuracy and faster reaction times (RT) with increasing motion strength.

Our data confirmed an inverse relationship between RT and motion strength.

We observe variations in accuracy and RT across different phases of the experiment. The data demonstrate a trend where accuracy generally increases and RT decreases as subjects progress through the phases. This pattern supports our hypothesis that as subjects gain experience and learning advances, they become more accurate and respond more quickly.

These findings underscore the effectiveness of the training and learning protocols implemented, indicating a positive correlation between the amount of practice and performance improvement. This aligns well with our expectations and provides valuable insights into the cognitive processing and decision-making enhancements that occur with increased familiarity with the task.

To validate the data, we fitted the accuracy and RT data to a Drift Diffusion Model (DDM). The model provided a good fit for the participants' psychometric and chronometric functions (Kolmogorov-Smirnov). However, interpreting this P-value can be challenging, and statistically significant misfits could occur. Therefore, we applied Monte Carlo simulations to address potential biases from statistical model tests. This validation demonstrated that the synthetic datasets and our original model did not significantly differ in their goodness of fit.

4 Discussion

The results of our study clearly demonstrate significant changes in decision-making parameters as subjects progress through the different phases of the RDM task. The observed increase in drift rate over the phases indicates that subjects become more efficient at processing information, resulting in faster and more accurate decisions. This improvement is likely due to enhanced perceptual sensitivity or better strategy use as the task becomes more familiar. Conversely, the reduction in decision boundary and non-decision time

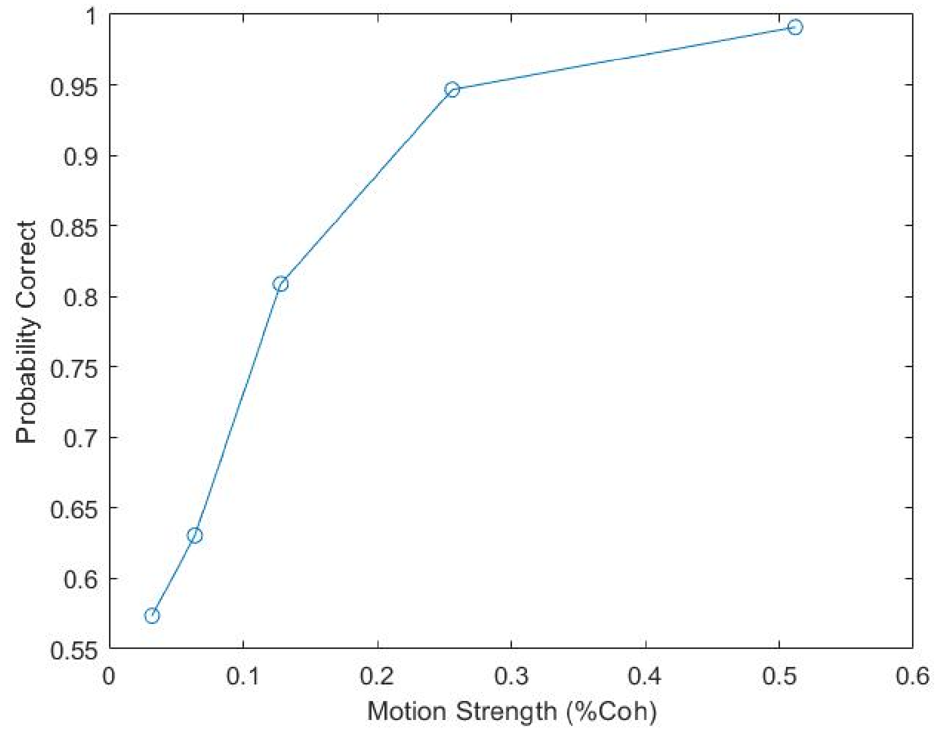

Figure 1: Accuracy of Our Subjects Across Different Coherencies

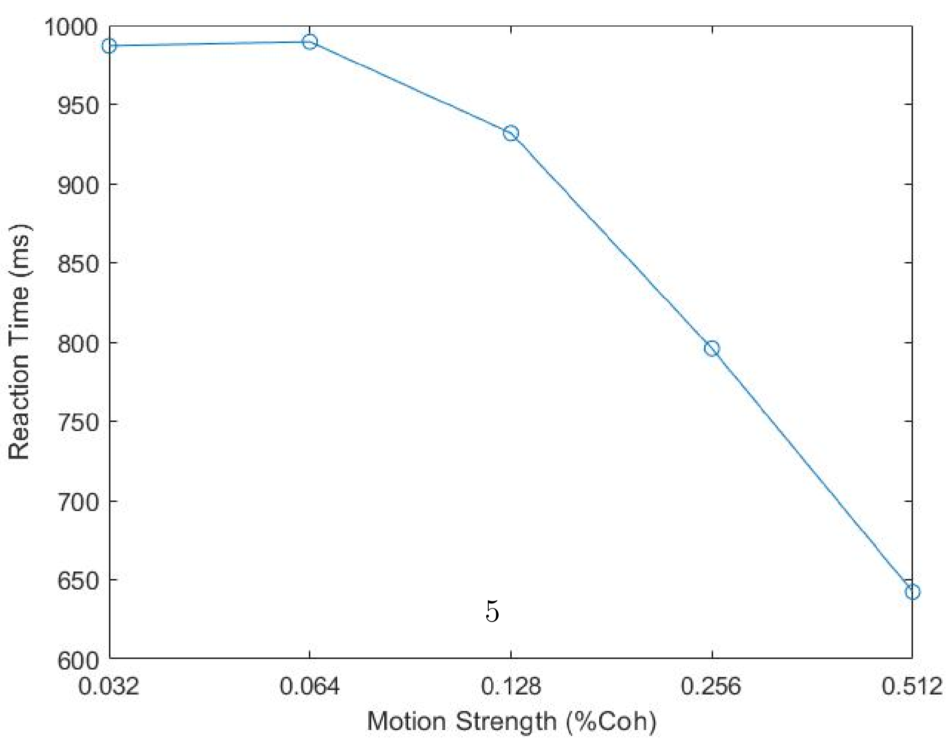

Figure 2: Reaction Time of Our Subjects Across Different Coherencies

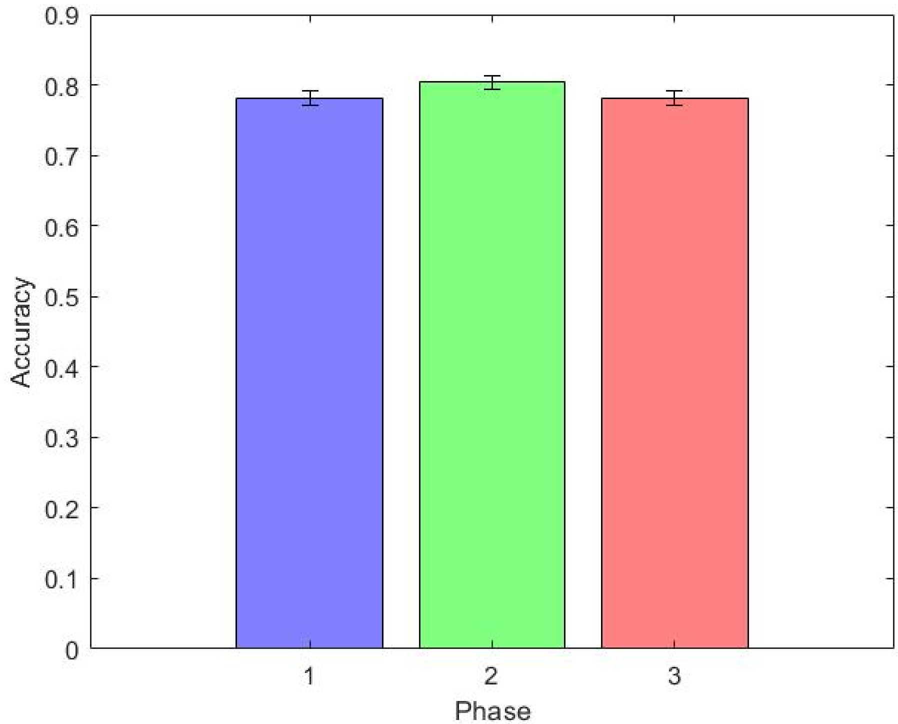

Figure 3: Accuracy of Our Subjects Across Different Phases

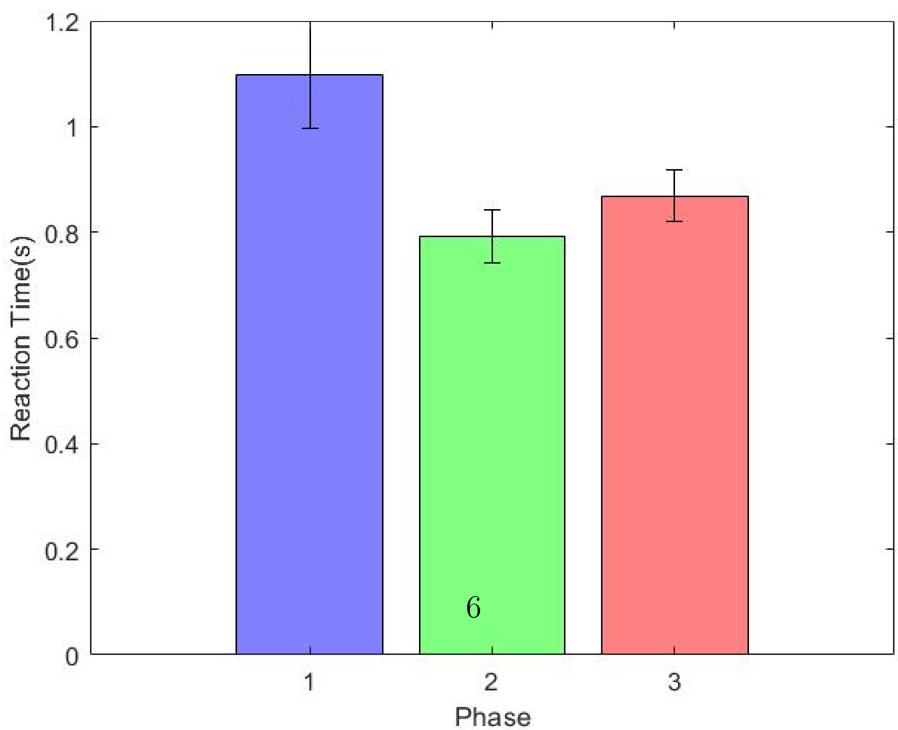

Figure 4: Reaction Time of Our Subjects Across Different Phases

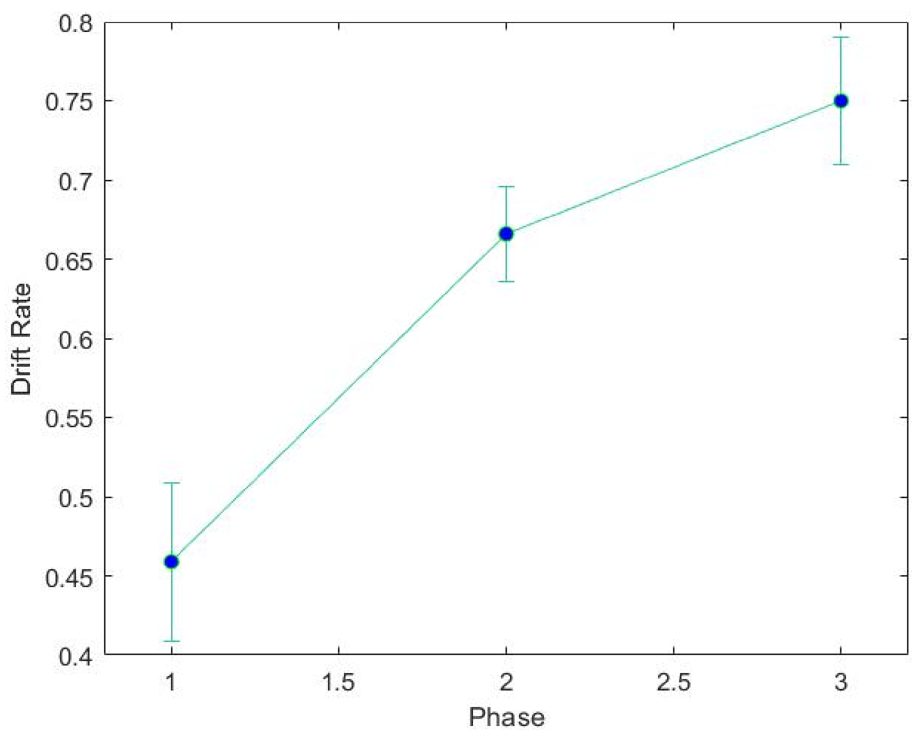

Figure 5: Drift Rate of Our fitted DDM Model Across Different Phases

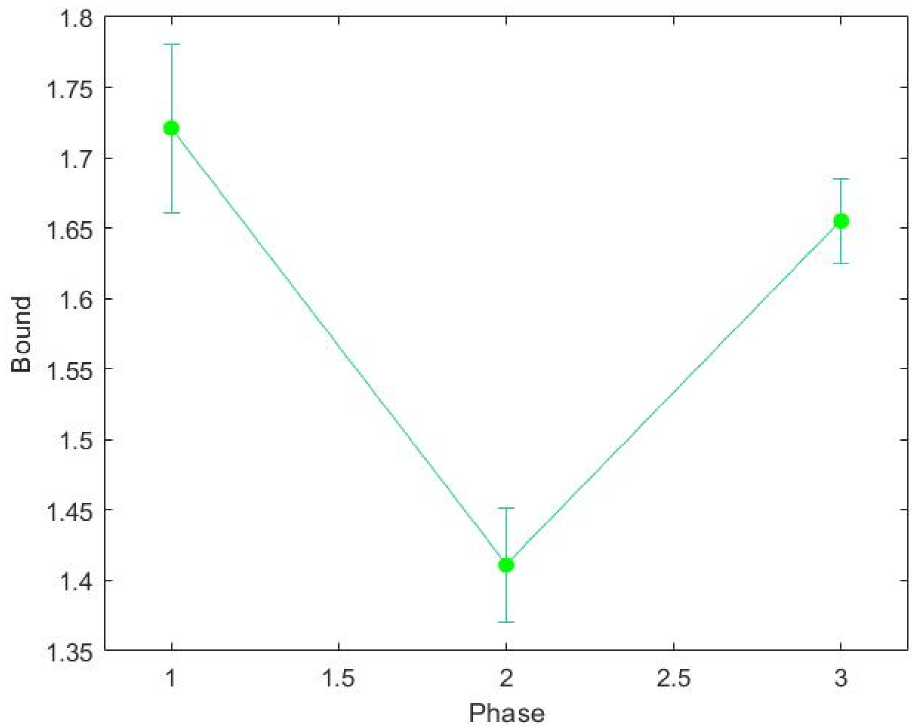

Figure 6: Bound of Our fitted DDM Model Across Different Phases

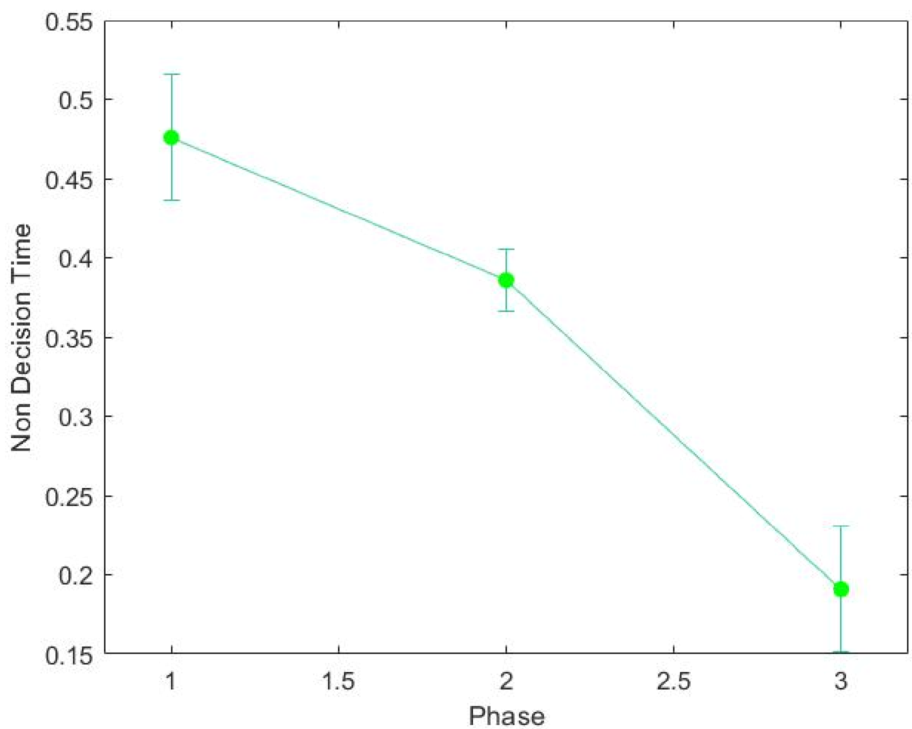

Figure 7: non Decision Time of Our fitted DDM Model Across Different Phases

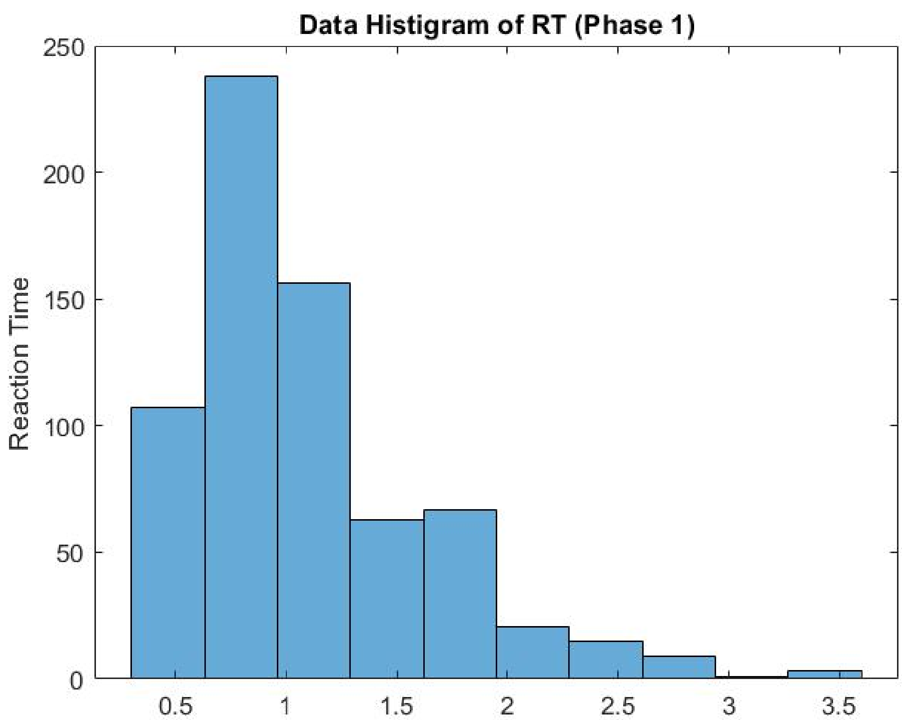

Figure 8: Histogram of Reaction Time of our data in Phase 1

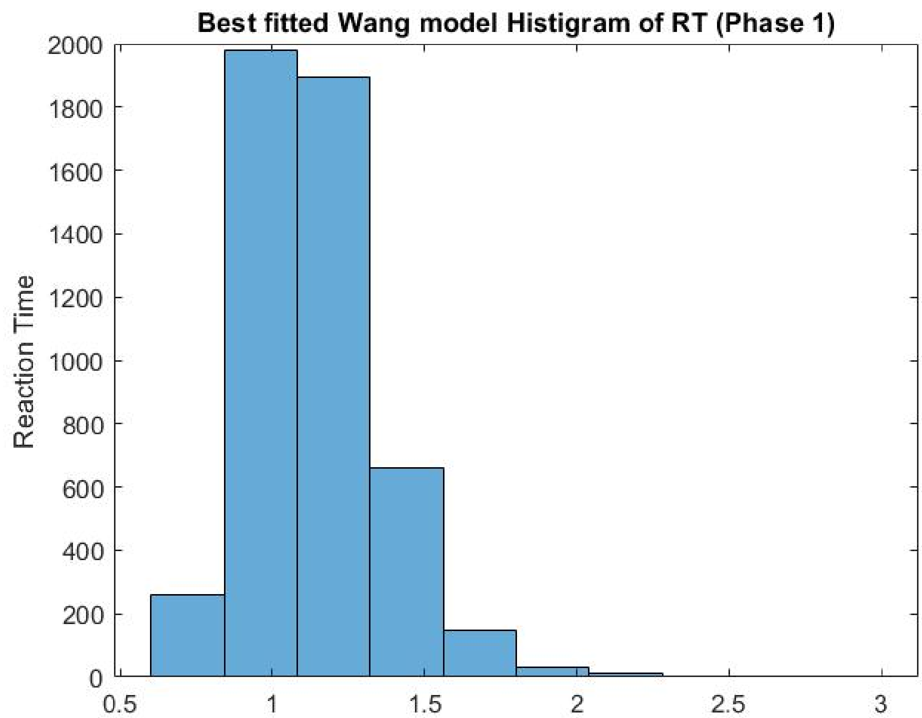

Figure 9: Histogram of Reaction Time Base on best fitted Wang model to Phase 1

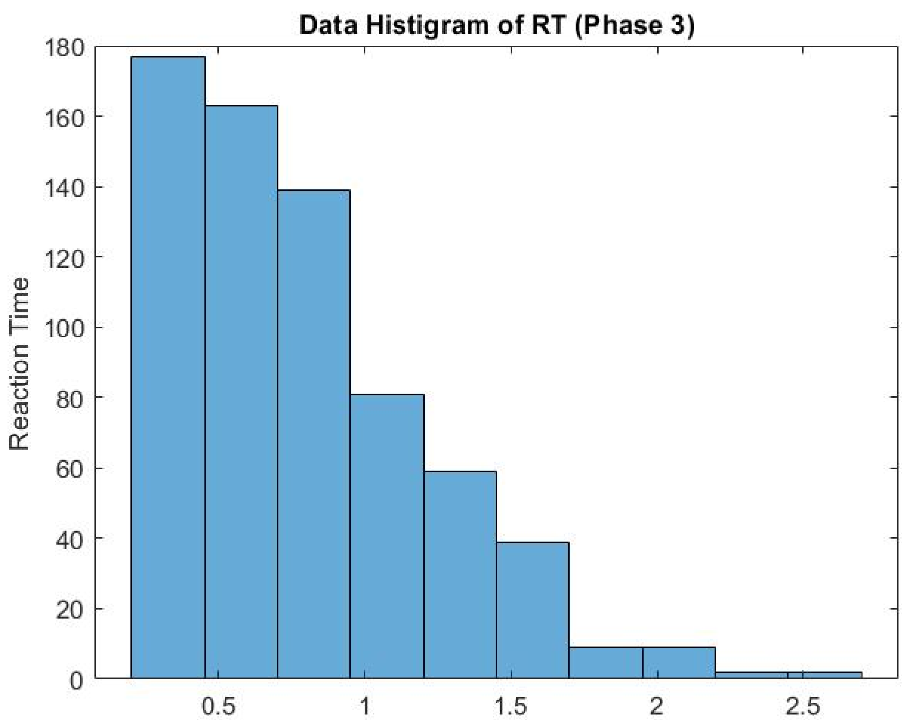

Figure 10: Histogram of Reaction Time of our data in Phase 3

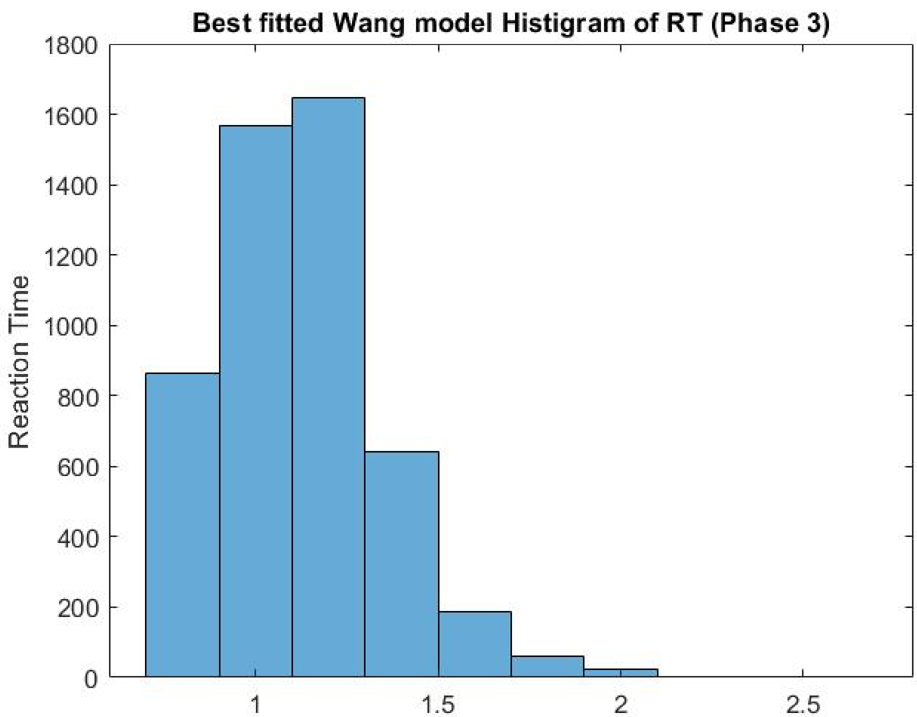

Figure 11: Histogram of Reaction Time Base on best fitted Wang model to Phase 3

with advancing phases suggests a shift towards quicker decision-making, potentially at the expense of caution, reflecting increased confidence in the judgments made.

5 Conclusion

Overall, our findings enhance the understanding of cognitive adaptations that occur with learning in decision-making tasks. They highlight the importance of accounting for changes in internal decision parameters when assessing the impact of practice and exposure on performance. Future research could investigate these dynamics in various populations or more complex decision-making scenarios to further elucidate the mechanisms of cognitive adaptation in perceptual decision-making.