Investigating Decision-Making Processes Using Drift Diffusion and Wang Models Across Learning Phases

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Abstract

Understanding how decision-making processes evolve with learning is crucial for cognitive neuroscience. In this study, we examined the changes in decision-making parameters across three distinct learning phases using two computational models: the Drift Diffusion Model (DDM) and the Wang Model. Data were collected from participants performing a series of tasks, segmented into early, middle, and late learning phases. We estimated key parameters such as drift rate, decision boundary, non-decision time for the DDM, and threshold and noise for the Wang Model. Our findings reveal systematic variations in these parameters, reflecting the dynamics of cognitive processes underlying decision-making. The results offer insights into how learning modulates the efficiency and consistency of decision-making, highlighting the interplay between cognitive adaptation and task performance. a nuanced understanding of the parallels and divergences between artificial and natural vision systems.

1 Introduction

The study of decision-making processes is fundamental in cognitive neuroscience, providing insights into how individuals process information and make choices. Computational models, such as the Drift Diffusion Model (DDM) and the Wang Model, have been instrumental in quantifying these processes.These models allow for the estimation of parameters that reflect the underlying cognitive mechanisms, such as drift rate, decision boundary, non-decision time, and noise.

Learning is known to influence decision-making processes. However, the nature of these changes across different phases of learning remains an area of active research. This study aims to investigate how decision-making parameters evolve over time by analyzing data from participants performing a decision-making task across three distinct learning phases: initial learning, mid-learning, and advanced learning.

2 Methodology

1.Participants

Data were collected from two participants(a male,62 and a female,26), each performing eight blocks of a decision-making task. The blocks were segmented into three phases: the first two blocks (Phase 1), the last two blocks (Phase 2), and the remaining four blocks (Phase 3).

2.Task and Procedure

Participants were required to make decisions based on random dot motion stimuli, with varying levels of coherence. The task measured reaction times and accuracy, providing the data necessary for model fitting.

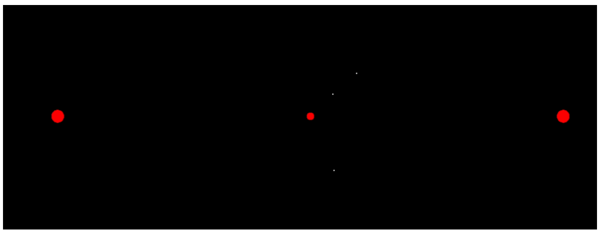

fig1.One frame of the task

3.Data Analysis

DWe used two computational models to analyze the data: the Drift Diffusion Model (DDM) and the Wang Model. For the DDM, we estimated the drift rate, decision boundary, and non-decision time using a custom fitting procedure. For the Wang Model, we estimated the threshold and noise parameters using an optimization approach .

Additionally, we plotted psychometric and chronometric functions to capture the accuracy and reaction time dynamics across different motion strengths.

3 Results

1.Psychometric and Chronometric Functions

The psychometric function showed how accuracy increased with higher motion coherence, reflecting improved perceptual sensitivity. The chronometric function depicted reaction time decreasing with higher coherence, indicating faster decision-making as the task became easier.

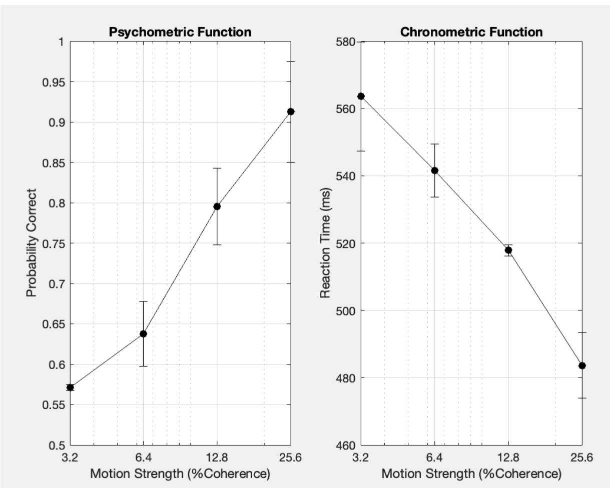

fig2.Psychometric and Chronometric Function

2.Drift Diffusion Model (DDM)

The DDM parameters showed systematic changes across the learning phases. The drift rate slightly decreased, indicating a subtle change in information processing efficiency across phases. The decision boundary increased, suggesting a higher threshold for making decisions. Non-decision time showed a slight decrease, reflecting faster motor processes as learning progressed.

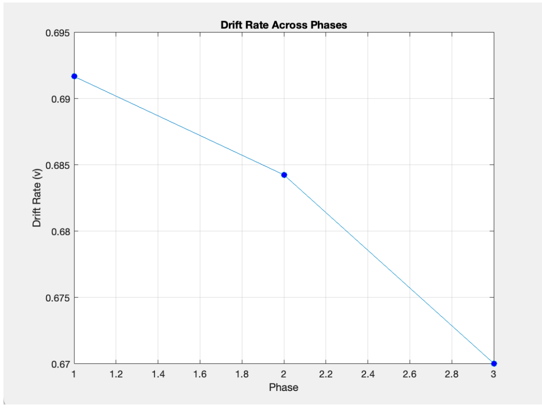

fig3.Drift Rate Across Phase

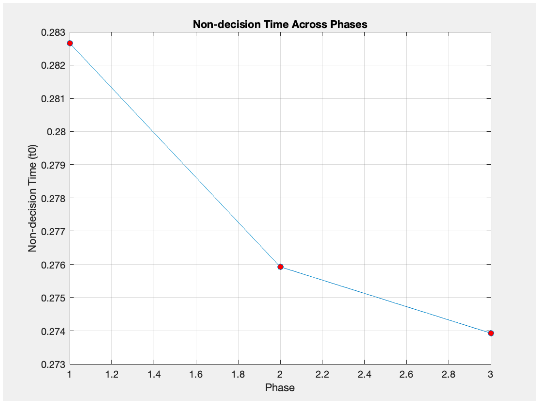

Fig4. Non-Decision Time Across Phase

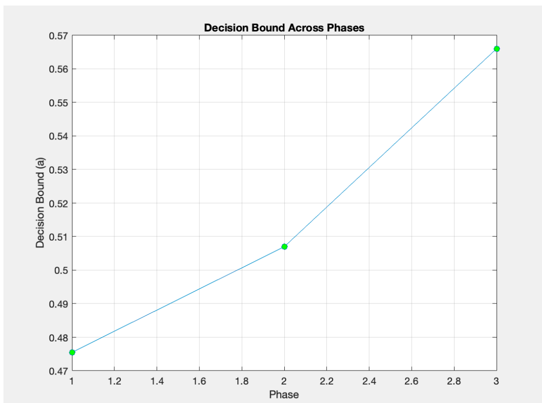

fig5.Decision Bound Across Phase

The drift rate slightly decreased from Phase 1 to Phase 3, indicating a subtle reduction in information processing efficiency over time

.The decision boundary increased from Phase 1 to Phase 3, suggesting that participants became more conservative in their decision-making.

Non-decision time slightly decreased across the phases, reflecting faster motor processes as participants became more familiar with the task.

3.Wang Model

The Wang Model parameters also exhibited notable changes. The threshold parameter decreased in the second phase, indicating a period of adjustment, followed by a stabilization in the third phase. The noise parameter increased in the second phase, suggesting greater variability during this period, and then decreased in the third phase, reflecting stabilization.

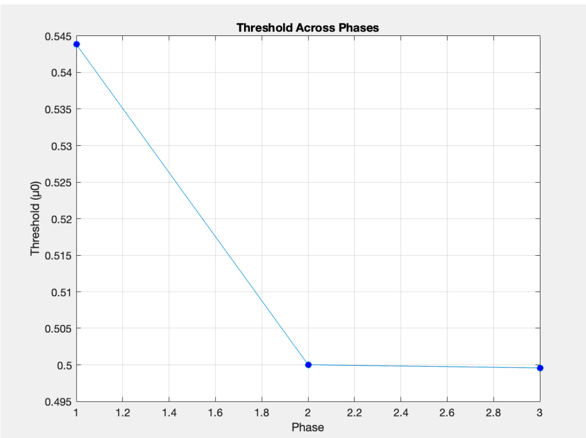

fig6.Threshold Across Phase

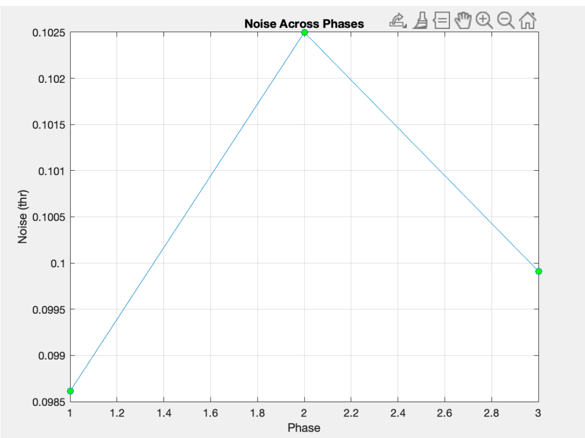

Fig7.Noise Across Phase

The threshold parameter decreased significantly in Phase 2 and stabilized in Phase 3, indicating an adjustment period followed by stabilization.

The noise parameter increased in Phase 2, suggesting greater variability during this period, and then decreased in Phase 3, reflecting stabilization.

4.Accuracy and Reaction Time Across Phases

he accuracy increased from Phase 1 to Phase 2 and slightly decreased in Phase 3, indicating an initial improvement and subsequent stabilization of performance.

Reaction time remained relatively stable across the phases, suggesting that the task difficulty was consistently managed by the participants.

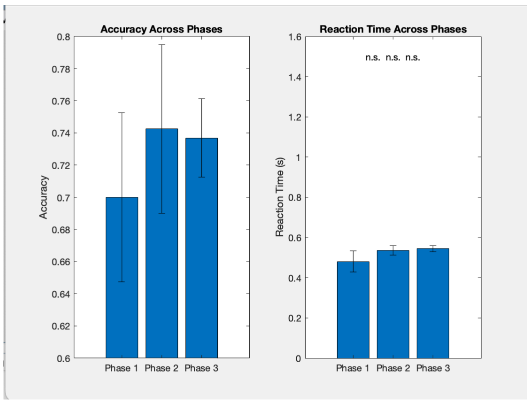

Fig9.Accuracy and Reaction TIme Across Phases

4 Discussion

Our findings highlight the dynamic nature of decision-making processes during learning. The slight decrease in drift rate and the increase in decision boundary across the phases suggest that participants became more conservative in their decision-making. The changes observed in the Wang Model parameters further support the notion of cognitive adaptation and stabilization over time.

The psychometric and chronometric functions provided additional insights into how perceptual sensitivity and decision speed evolved with learning. The increase in accuracy and decrease in reaction time with higher motion coherence reflect enhanced perceptual processing and faster decision-making as participants became more familiar with the task.

6 Conclusion

This study demonstrates how computational models can be used to uncover the nuances of decision-making processes across different learning phases. The systematic changes in model parameters provide valuable insights into the cognitive mechanisms underlying learning and decision-making. These findings contribute to a deeper understanding of how individuals adapt their cognitive strategies in response to task demands and learning experiences.

6 References

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