A Study on RDM Perception and Decision-Making Models

Saeed Mansur Lakuraj

[1]Sharif University Of Technology

saeed.mansoorri@gmail.com

Abstract -

This study investigates the dynamics of learning in the context of the Random Dot Motion (RDM) task, focusing on the evolution of reaction times and accuracy across three distinct phases of practice. Our primary objective is to elucidate how repeated exposure to the RDM task influences decision-making efficiency.

We collected comprehensive RDM data, analyzing participants' performance to observe the effects of learning. As hypothesized, results indicated a significant decrease in mean reaction time and an increase in accuracy, reflecting enhanced decision-making proficiency over time. To further interpret these findings, we applied the Wang model and the Drift Diffusion Model (DDM) to the data.

Model fitting revealed that with practice, participants exhibited an increased drift rate, suggesting more efficient evidence accumulation. Additionally, there was a noticeable reduction in decision bound and non-decision time, indicative of streamlined decision processes. These results underscore the cognitive adaptations that occur through repeated task exposure.

This study provides valuable insights into the cognitive mechanisms underpinning perceptual decision-making and highlights the impact of learning on improving decision efficiency.

Keywords -

decision making ,RDM, accuracy, traction time, wang model, DDM,improving decision efficiency

1 Introduction

Perceptual decision-making is a fundamental cognitive process that involves interpreting and responding to sensory stimuli. One of the most effective paradigms to study this process is the Random Dot Motion (RDM) task, where individuals discern the direction of coherent motion in a dynamic field of randomly moving dots. This task is particularly useful due to its capacity to precisely control task difficulty and thus provide detailed insights into the decision-making process.

Decision-making is the process of selecting a course of action from multiple alternatives based on available information. In the context of the RDM task, this involves interpreting the motion direction of dots and making a choice accordingly. Two critical metrics for assessing performance in decision-making tasks are reaction time and accuracy.

- Reaction Time: This refers to the time elapsed between the presentation of the stimulus and the participant's response. It is a crucial measure of processing speed and efficiency in decision-making. Shorter reaction times typically indicate quicker information processing and decision execution.
- Accuracy: This metric represents the proportion of correct responses made by the participant. Higher accuracy indicates better perceptual sensitivity and decision accuracy, reflecting the participant's ability to correctly interpret and respond to the stimulus.

This study, titled "A Study on RDM Perception and Decision-Making Models," investigates how perceptual decision-making evolves through learning. Specifically, it examines changes in mean reaction time and accuracy across three phases of practice, utilizing both behavioral data and advanced computational models to uncover underlying cognitive and neural mechanisms. The primary objectives of this research are:

1. To quantify the effects of learning on perceptual decision-making by monitoring changes in reaction time and accuracy.

   To model these behavioral changes using the Drift Diffusion Model (DDM) and Wang model.
2. To analyze how parameters such as drift rate, decision bound, and non-decision time vary with practice and learning.

We hypothesize that learning will lead to decreased reaction times and increased accuracy, indicative of enhanced decision-making efficiency. These improvements will be reflected in the DDM as an increased drift rate (indicating faster evidence accumulation) and decreased decision bound and non-decision time (indicating more efficient decision thresholds and processing times). Wang's model will further elucidate the neural mechanisms behind these behavioral changes, particularly focusing on the roles of NMDA receptor-mediated excitatory reverberation and recurrent network dynamics.

Several studies have explored the neural and cognitive mechanisms underlying perceptual decision-making. For instance, Roitman and Shadlen (2002) found that the lateral intraparietal cortex (LIP) plays a critical role in accumulating sensory evidence during the RDM task, with neural activity ramping up until a decision threshold is reached. Their work highlighted the importance of evidence accumulation in decision-making, correlating neural activity with behavioral outcomes such as reaction time and accuracy.

This study aims to provide comprehensive insights into how perceptual decision-making improves with learning. By analyzing both behavioral data and computational models, we seek to understand the cognitive and neural adaptations that facilitate more efficient decision-making. The findings will contribute to the broader field of cognitive neuroscience by offering detailed mechanisms of how practice influences perceptual decisions. Moreover, these insights have potential applications in developing training programs and interventions to enhance decision-making skills in various practical domains.

2 Methodology

This section details the methodology employed in our study on RDM perception and decision-making models. The methodology is divided into three parts: Participants, Stimuli and Procedure, and Data Collection.

2.1 Participants

Three participants were recruited for the RDM (Random Dot Motion) task. The participants included two men and one woman, with an age range of 34 ± 19 years. All participants had good visual acuity, though two of them required corrective lenses. And all of their data has been examined and were reliable.

2.2 Stimuli and Procedure

The RDM task was created using Psychtoolbox, a MATLAB-based tool for designing and running psychological experiments. Participants sat in front of a laptop screen in a quiet room. The experimental procedure involved the following steps:

1. Fixation Point: Each trial began with a fixation point displayed at the center of the screen, which participants were instructed to focus on. This fixation point ensured that participants started each trial with their gaze directed correctly.

2. Stimulus Presentation: After the participant pressed the space bar, the RDM stimulus was presented on the screen for 1.5 seconds. The stimulus consisted of dots moving in a random pattern, with a certain percentage moving coherently in one direction. The levels of coherence used were 3.2%, 6.4%, 12.8%, and 25.6%, representing the proportion of dots moving coherently versus randomly.

3. Response: During the 1.5-second interval, participants were required to press either the left or right arrow key on the keyboard to indicate their decision about the direction of coherent motion.

4. Feedback: Immediately after the response or the lapse of the 1.5-second interval, participants received feedback via a sound indicating whether their decision was correct or incorrect.

5. After the feedback, the next trial began.

There were 200 trials per block, and participants completed 8 blocks in total. The first two blocks constituted Phase 1, the last two blocks Phase 3, and the remaining four blocks Phase 2.

3 Models and Data Analysis

3.1 Reaction Time and Accuracy Based on Coherence

In the Random Dot Motion (RDM) task, coherence levels significantly affect both reaction time and accuracy. We analyzed the data across four levels of coherence: 3.2%, 6.4%, 12.8%, and 25.6%.

As seen in the plot, there is an unexpected increase in reaction time at the 6.4% coherence level compared to the 3.2% level. This anomaly can be interpreted by considering the cognitive load and decision-making strategies at low coherence levels. At 3.2%, the motion signal is extremely weak, leading participants to primarily guess, resulting in relatively fast, albeit random, responses. However, at 6.4% coherence, the motion signal is slightly stronger, prompting participants to engage more cognitive resources to discern the direction. This effort to process the information more carefully can lead to a temporary increase in reaction time. Once coherence increases further to 12.8% and 25.6%, the motion direction becomes clearer, allowing participants to make faster and more confident decisions, thereby reducing reaction time.

Accuracy, measured as the proportion of correct responses, increases with the coherence level, as shown in the plot. At the lowest coherence level (3.2%), accuracy hovers around chance level, indicating that participants are largely guessing. As coherence increases, accuracy improves significantly, reflecting better perceptual discrimination of the motion direction.

The slight dip in accuracy at the 6.4% coherence level compared to 3.2% can be explained by the participants' shift from random guessing to more deliberate processing. While their increased effort does not immediately translate to higher accuracy at 6.4%, it sets the stage for subsequent improvements at higher coherence levels (12.8% and 25.6%). This trend underscores the cognitive transition phase where participants move from guesswork to more accurate perceptual judgments.

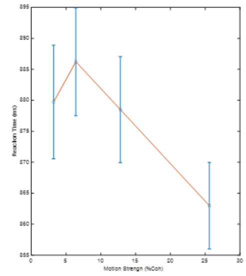

Figure 1: Reaction Time and Accuracy Based on Coherence (Right image is Reaction Time based on Coherence levels and left image is Accuracy Based on Coherence level)

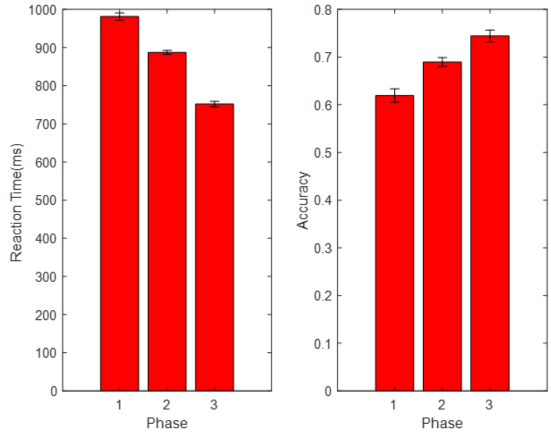

Figure 2: reaction time and accuracy per phase (we can see effect of learning in learning)

3.2 Reaction Time and Accuracy Based on Phase

The analysis of reaction time (RT) and accuracy across different phases of the study provides insights into how learning influences decision-making performance in the Random Dot Motion (RDM) task. Participants completed the RDM task in three phases: Phase 1 (blocks 1 and 2), Phase 2 (blocks 3 to 6), and Phase 3 (blocks 7 and 8).

3.2.1 Performance Across Phases

As depicted in Fig. 2, there is a noticeable improvement in both reaction time and accuracy as participants progress through the phases. Specifically, accuracy increases and reaction time decreases from Phase 1 to Phase 3. This trend is indicative of learning effects, where participants become more proficient at the task with practice. The improvement in accuracy suggests that participants are better at discerning the direction of motion, while the reduction in reaction time reflects faster decision-making processes.

This learning effect is attributed to participants adjusting their decision-making strategies as they gain more experience with the task. Initially, in Phase 1, participants are likely familiarizing themselves with the task requirements and stimulus properties. By Phase 2, they have developed more effective strategies for processing the motion stimuli, leading to quicker and more accurate responses. In Phase 3, these strategies are further refined, resulting in optimal performance.

3.2.2 Reaction Time Distribution Analysis

To further investigate whether reaction time distributions can distinguish between the phases, we plotted normalized histograms of reaction times with 20 bins for each phase Fig. 3. Additionally, boxplots of reaction times for each phase were generated Fig. 4. Visual inspection of these plots suggests that Phase 1 can be clearly discriminated from Phases 2 and 3 based on reaction time distributions. To statistically validate these observations, we

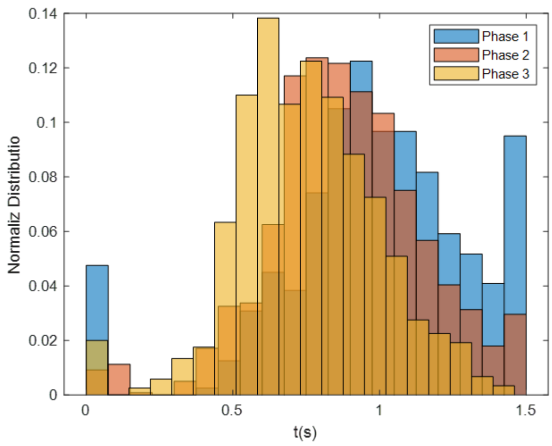

Figure 3: Distribution of reaction time in different phases (we have used normalize histogram because number of blocks in phase 2 is not same as to other blocks)

conducted two-sample t-tests (t-test2) comparing reaction times between each pair of phases. The two-sample t-test is appropriate here as the reaction times in different phases have different sample sizes. The results of the t-tests revealed significant differences between all pairs of phases (Phase 1 vs. Phase 2, Phase 1 vs. Phase 3, and Phase 2 vs. Phase 3), with p-values approaching zero and the null hypothesis (h) being rejected in each case (h=1). These findings confirm that not only can we visually discriminate the phases based on reaction time distributions, but these differences are also statistically significant. The decrease in reaction time and the increase in accuracy across phases highlight the impact of learning on participants' decision-making efficiency.

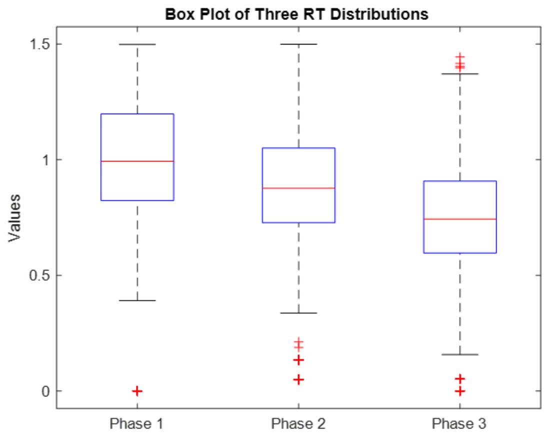

Figure 4: visualization of Reaction Time Distribution Analysis using box plots

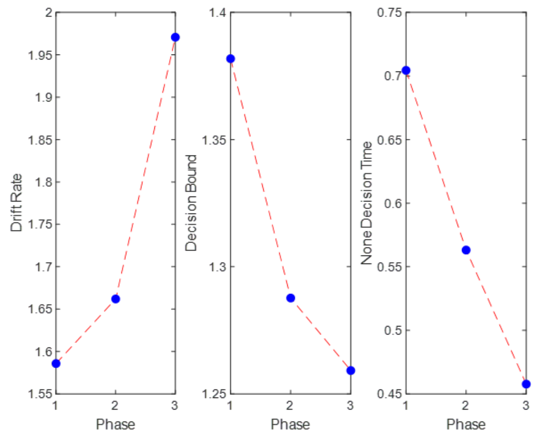

Figure 5: Changes in Drift Diffusion Model parameters across phases. The drift rate (v) increases, the decision bound (a) decreases, and the non-decision time (Ter) decreases as participants progress through the phases, indicating improved decision-making efficiency with learning.

3.3 Drift Diffusion Model

The Drift Diffusion Model (DDM) is a prominent computational model used to describe the decision-making process in tasks such as the Random Dot Motion (RDM) task. The DDM conceptualizes decision-making as a process where noisy evidence accumulates over time until it reaches one of two decision boundaries, leading to a response. The model is characterized by several key parameters:

- **Drift Rate (v)**: This parameter represents the average rate at which evidence accumulates. A higher drift rate indicates faster evidence accumulation, leading to quicker and more accurate decisions.
- **decision bound (a)**: This parameter defines the amount of evidence required to make a decision. Larger decision bounds mean more conservative decision-making, requiring more evidence before a decision is made.
- **Non-decision Time (Ter)**: This parameter accounts for the time consumed by processes other than decision-making, such as sensory encoding and motor response.

To analyze the data collected from the RDM task across different phases, we employed the Fast-DM software, a tool designed for fitting the DDM to empirical data. Using the correctness and reaction time data, we optimized the model parameters using both Kolmogorov-Smirnov (KS) and Chi-Square (CS) optimization methods. The results indicated significant changes in the model parameters across the learning phases.

Changes in DDM Parameters Across Phases

The DDM parameters showed systematic changes as participants progressed through the phases, reflecting the learning effects observed in the behavioral data. Specifically:

- **Drift Rate (v) Increasing**:
  - **Phase 1**: Initially, participants have a lower drift rate, indicating slower evidence accumulation due to their unfamiliarity with the task.
  - **Phase 2**: As participants become more familiar with the task, the drift rate increases, reflecting improved efficiency in processing the motion direction.
  - **Phase 3**: By the final phase, the drift rate is at its highest, indicating that participants have optimized their evidence accumulation process, leading to faster and more accurate decisions.
- **decision bound (a) Decreasing**:
  - **Phase 1**: Participants start with a larger decision bound, indicating a more cautious decision-making strategy, requiring more evidence before making a choice.
  - **Phase 2**: With practice, participants become more confident and reduce their decision boundaries, reflecting a shift towards a more balanced decision-making strategy.
  - **Phase 3**: In the final phase, the decision bound is the smallest, indicating that participants are making decisions more quickly and with less accumulated evidence, a sign of improved decision-making efficiency.
- **Non-decision Time Decreasing**:

- **Phase 1**: The non-decision time is initially higher, accounting for longer periods spent on sensory encoding and motor response due to unfamiliarity with the task setup.
- **Phase 2**: As participants gain experience, the non-decision time decreases, reflecting faster sensory and motor processes.
- **Phase 3**: By the final phase, non-decision time is minimized, indicating that participants have become highly efficient in these processes, contributing to overall faster reaction times.

The observed changes in DDM parameters align with the expected learning effects, where participants become more efficient and confident in their decision-making process with practice. The increasing drift rate, decreasing decision boundary, and decreasing non-decision time collectively illustrate how learning and familiarity with the task enhance perceptual decision-making efficiency.

These results are visually represented in Fig. 5, showing the progression of DDM parameters across the three phases. The systematic changes in these parameters underscore the utility of the DDM in capturing the dynamics of learning and decision-making processes.

3.4 Wang Model

The Wang model, a recurrent neural network model, is a powerful framework for understanding the neural mechanisms underlying decision-making processes. This model emphasizes the role of excitatory and inhibitory interactions within neural circuits to explain how decisions are formed based on sensory evidence. The Wang model is particularly useful for simulating how changes in neural activity correlate with behavioral outcomes such as reaction time and accuracy.

For this part of the analysis, we focused on optimizing the Wang model parameters for Phases 1 and 3 to understand how learning influences neural decision-making dynamics. The optimization process involved adjusting two free parameters—u_0 (the input strength) and the decision threshold—along with other parameters, to minimize the sum of mean squared errors (MSE) between the model's predictions and the empirical data for each phase.

Optimization Process

The optimization was carried out using the `fminsearch` function, a derivative-free method for finding the minimum of an unconstrained multivariable function. Each optimization run consisted of 150 epochs and was repeated at least 50 times to ensure robustness. The objective was to find the parameter set that best matched the reaction time and accuracy data from the RDM task for Phases 1 and 3.

Phase 1 Optimization Results

For Phase 1, the best-fitting parameters were:

- **Threshold (thr)**: 0.45
- **Input Strength (u_0)**: 30
- **Coherence (coh)**: 12.8%
- **Standard Deviation of Noise (SDnoise)**: 0.3
- **Non-decision Time**: 0.7
- **Baseline Activity**: 0.18

These parameters resulted in an accuracy of 0.54, closely matching the observed accuracy for Phase 1 of approximately 0.6. The t-test comparing the reaction time distributions of the model and the empirical data(Fig. 6) yielded $h = 0$ and $p = 0.2249$, indicating no significant difference between the model and the empirical data distributions. This suggests that the model accurately captures the decision-making dynamics for Phase 1.

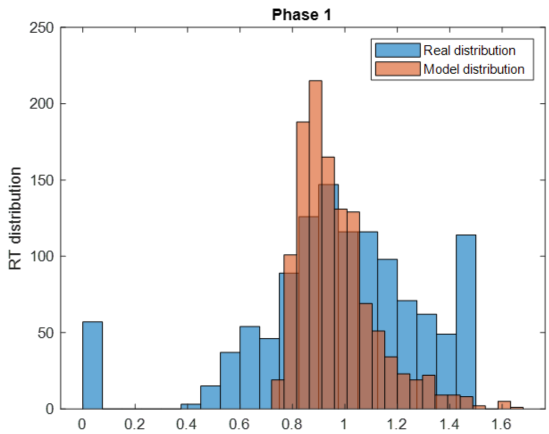

Figure 6: Rt Distribution of model and phase 1 data ($h = 0$ and $p = 0.2249$)

Phase 3 Optimization Results

For Phase 3, the best-fitting parameters were:

- **Threshold (thr)**: 0.25
- **Input Strength (u_0)**: 25
- **Coherence (coh)**: 25.6%
- **Standard Deviation of Noise (SDnoise)**: 0.07
- **Non-decision Time**: 0.48
- **Baseline Activity**: 0.3

These parameters resulted in an accuracy of 0.8, closely matching the observed accuracy for Phase 3 of approximately 0.74. The t-test comparing the reaction time distributions of the model and the empirical data (Fig. 7)

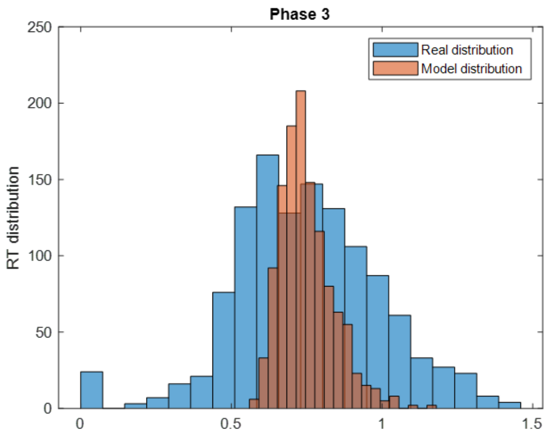

Figure 7: Rt Distribution of model and phase 3 data (h = 0 and p = 0.7389)

yielded $h = 0$ and $p = 0.7389$, again indicating no significant difference between the model and the empirical data distributions.

Interpretation of Results

The differences in the optimized parameters between Phases 1 and 3 reflect the impact of learning on the neural decision-making process:

- **Threshold (thr)**: The lower threshold in Phase 3 (0.25) compared to Phase 1 (0.45) indicates that participants required less evidence to make a decision after learning. This suggests a more efficient decision-making process as participants became more familiar with the task.

- **Input Strength** (u_0): The decrease in input strength from Phase 1 to Phase 3 (30 to 25) may reflect a reduction in the effort required to process the motion signal, as participants become more adept at interpreting the stimuli.

- **Non-decision Time**: The reduction in non-decision time from Phase 1 to Phase 3 (0.7 to 0.48) highlights improvements in sensory encoding and motor response times due to learning.

- **Baseline Activity**: The increase in baseline activity from Phase 1 to Phase 3 (0.18 to 0.3) suggests an enhanced readiness or preparatory activity in the neural circuits involved in decision-making.

The results from the t-tests ($h = 0$ with p values of 0.2249 for Phase 1 and 0.7389 for Phase 3) indicate that the model's reaction time distributions are not significantly different from the empirical data. This supports the validity of the Wang model in accurately simulating the decision-making process across different phases of learning.

These findings demonstrate the utility of the Wang model in capturing the nuanced changes in decision-making dynamics due to learning, providing a deeper understanding of the underlying neural mechanisms.

Table 1: Summary of Optimized Wang Model Parameters for Phases 1 and 3

Parameter	**Phase 1**	**Phase 3**
Threshold (thr)	0.45	0.25
Input Strength (u_0)	30	25
Coherence (coh)	12.8%	25.6%
Standard Deviation of Noise (SDnoise)	0.3	0.07
Non-decision Time (Ter)	0.7	0.48
Baseline Activity	0.18	0.3
Accuracy	0.54	0.8
Empirical Accuracy	0.6	0.74
t-test h	0	0
t-test p	0.2249	0.7389

4 Conclusion

This study aimed to elucidate the mechanisms underlying perceptual decision-making using the Random Dot Motion (RDM) task and to investigate how learning affects these processes. By examining reaction times, accuracy, and fitting behavioral data to computational models, we gained comprehensive insights into the cognitive and neural adaptations that occur with practice.

4.1 Key Findings

- **Reaction Time and Accuracy Across Coherence Levels**: As coherence levels increased, participants' reaction times decreased and accuracy improved, demonstrating that higher motion clarity facilitates quicker and more accurate decisions. The slight anomaly at the 6.4% coherence level, where reaction time increased temporarily, is likely due to participants transitioning from random guessing to more deliberate processing of motion direction.

- **Learning Effects on Performance Across Phases**: Significant improvements in reaction time and accuracy were observed across the three phases of the task. These improvements indicate that participants became more proficient and efficient in their decision-making with practice. Visual and statistical analyses of reaction time distributions further confirmed that the learning effects were substantial and statistically significant.

- **Drift Diffusion Model (DDM) Analysis**: The DDM parameters revealed systematic changes due to learning. Specifically, the drift rate increased, indicating faster evidence accumulation; the boundary separation decreased, reflecting more efficient decision thresholds; and the non-decision time decreased, highlighting faster sensory encoding and motor response times. These changes collectively illustrate how learning enhances perceptual decision-making efficiency.

- **Wang Model Analysis**: For Phases 1 and 3, the Wang model was optimized to fit the reaction time and accuracy data. The optimization process involved adjusting parameters such as threshold and input strength. The results showed a lower threshold and input strength in Phase 3 compared to Phase 1, indicating that participants required less evidence and exerted less effort to make decisions after learning. The non-decision time also decreased, and baseline activity increased, reflecting enhanced readiness and efficiency in decision-making processes. The model's accuracy closely matched the empirical data, and the t-tests indicated no significant differences between the model and empirical distributions, supporting the model's validity.

4.2 Implications

The findings from this study have several important implications:

- **Cognitive Neuroscience**: The detailed analysis of reaction times and accuracy, along with the application of computational models, provides a deeper understanding of the neural and cognitive mechanisms underlying perceptual decision-making. The observed improvements in DDM parameters and Wang model fits highlight how practice and learning shape decision-making processes.

- **Practical Applications**: Insights from this study can inform the development of training programs and interventions aimed at improving decision-making skills. By understanding the specific cognitive and neural changes that occur with practice, targeted strategies can be designed to enhance performance in various applied settings, such as education, sports, and professional training.

- **Future Research**: This study sets the stage for further research into the neural correlates of decision-making. Future studies could explore the neural activity associated with the observed behavioral changes using techniques such as functional MRI or EEG. Additionally, investigating the effects of different types of training on decision-making efficiency could provide valuable information for optimizing learning strategies.

In conclusion, this study provides a comprehensive analysis of how learning influences perceptual decision-making in the RDM task. By integrating behavioral data with sophisticated computational models, we have demonstrated the cognitive and neural adaptations that occur with practice. The findings contribute significantly to our understanding of decision-making processes and have broad implications for enhancing performance through targeted training and interventions.

References