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Dynamic selection in the context of perceptual decision making

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Abstract

This thesis explores the limitations of the two-alternative forced-choice (2AFC) paradigm in decision-making research and proposes a novel approach incorporating continuous choices. The motivation stems from the need to better reflect the complexity of real-life decision-making scenarios. An extended experimental paradigm was developed, incorporating both traditional 2AFC tasks and a continuous decision-making task using random dot motion (RDM) stimuli. The results reveal distinct sensory mechanisms between the two tasks, highlighting the shortcomings of the 2AFC paradigm. Additionally, participants exhibit better performance with horizontal movements in the multiple-choice task, supporting the hypothesis of biomechanical influences on decision-making. Furthermore, the perceptual paradigm with multiple choices uncovered a latent phenomenon in the 2AFC task—a visual illusion resulting in a bimodal error angle distribution which remains relatively unexplained and under-reported.

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Acronyms

2AFC Two-Alternative Forced Choice

ACC Anterior Cingulate Cortex

dlPFC Dorsolateral Prefrontal Cortex

DT Decision Time

KINARM Kinarm end-point robotic device

LIP Lateral Intraparietal

M1 Primary Motor Cortex

MIP Medial Intraparietal Area

MT Middle Temporal

OFC Orbitofrontal Cortex

PPC Posterior Parietal Cortex

PRR Parietal Reach Region

RDM Random Dot Motion

RF Response Field

RT Reaction Time

SC Superior Colliculus

V1 Primary Visual Cortex

vmPFC Ventromedial Prefrontal Cortex

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Chapter 1

Introduction

In our daily lives, we encounter numerous decisions, ranging from banal choices to pivotal ones that shape our future. A study by Lightspeed Research conducted in November 2017 across ten European countries revealed that the average person makes around 35,000 decisions each day. This study found that individuals are conscious of only 0.26% of the decisions made by their brains, highlighting the significant role of unconscious processes in our decision-making [24]. This area is intensely studied within cognitive neuroscience, where a primary long-term goal is to elucidate the neural mechanisms underlying the decision-making process. It remains unclear how decisions are represented in the human brain and which specific brain regions are involved in orchestrating these processes. [19]

Decision-making requires the brain to accurately represent inputs and potential outcomes, including the values assigned to various options. A mechanism for selecting one option over others is necessary, feedback that can enhance performance through learning across multiple attempts can be an asset. This process engages various brain systems and involves both conscious and unconscious processes. [36]

In this thesis, we focus on the dynamic selection between different options in the context of perceptual decision making. Perceptual decisions often lead to immediate actions, making it easier to link sensory input with motor output, thereby simplifying the understanding of the decision-making process. Moreover, perceptual tasks, being highly controllable in experimental settings, allow for precise manipulation of variables and measurement of their effects on decision outcomes. By concentrating on perceptual decisions, we minimize the influence of higher-order cognitive processes, such as memory and emotional biases, which could complicate result interpretation. The dynamic selection aspect of the experimental task involves temporal elements where decisions evolve over time as more information becomes available, aiming at detecting the moment when a participant commits to a decision by performing a movement.

The intricacies of decision-making have captivated researchers, leading to the development of various theoretical models. Decision-making studies have shown that, under a broad set of conditions, individuals often combine a prior belief and a likelihood to make decisions under uncertainty. According to this viewpoint, the brain needs time to aggregate enough evidence favoring one alternative over the other before reaching the critical amount of evidence that allows for making the decision.

One prominent model, commonly known as competition through common inhibition, posits that neural populations integrate sensory information until a threshold activity is reached, triggering a commitment to a specific action. This theory, rooted in the Two-Alternative Forced Choice (2AFC) paradigm, has shaped our understanding of decision-making in humans and animals.

The 2AFC task is one of the simplest decision task that researchers have used to examine decision making in a broad range of disciplines. In this paradigm, participants are presented with two distinct alternatives and must select the one that meets a specific criterion. Examples in visual perception studies include choosing between two lines based on length [21], two circles based on color saturation [27], or two directions based on the predominant movement of dots in an circular aperture [22], known as the Random Dot Motion (RDM) stimulus. This stimulus, extensively used in studies with both humans and monkeys, is pivotal in exploring the neural basis of decision-making and perceptual processes. Moreover, the RDM task requires a single stimulus presentation and thus eliminates the need for working memory. This classic visual motion discrimination paradigm forms the experimental basis of this thesis.

However, 2AFC tasks do not fully capture the complexity and variability inherent in real-life decision-making scenarios. One significant limitation is that real-world decisions often require selecting from more than just two options. The purpose of this thesis is to gather and analyse relevant observations from an experimental study that compared decision-related behavior in 2AFC tasks with those involving multiple-choice scenarios. The collected data can later be used to validate —or invalidate— models designed based on 2AFC experiment.

Chapter 2 of this thesis is dedicated to the collection of documents reviewed to contextualize the advancements in scientific research on, on one hand, the neural mechanisms and brain regions involved in perceptual decision-making and, on the other hand, the various methods scientists have used to evolve the standard 2AFC RDM paradigm into multiple-choice decision making. The information presented in this section of the state-of-the-art is not exhaustive but is sufficiently comprehensive to understand the analyses and results obtained throughout this thesis.

Chapter 3 focuses on the two experimental tasks implemented in the context of this thesis. We collected behavioral data in a 2AFC task where the difficulty varied according to three levels of coherence and three levels of stimulus exposure duration. We also collected data in a multiple-choice task with a continuous decision space, where all trials tested in 2AFC are also presented to the participants in the multiple-choice task. The protocol and materials used in these experiments is presented, as well as the manner in which the data are extracted, collected, and utilized. The statistical tools used are described rigorously.

Chapter 4 is dedicated to the results obtained from the two experiments, grouped into several sections.

In the first Section, we analyze the results of the multiple-choice decision-making task. The observations obtained regarding the influence of different levels of coherence and stimulus exposure duration on participants' performances are in line with the expectations based on the scientific literature presented in the state-of-the-art.

While Section 1 deals solely with multiple-choice decisions, in Section 2, we compare the behavioral data from the 2AFC task with the corresponding trials in the multiple-choice task. This reveals how instructions such as the number of targets can influence performance on similar perceptual tasks. As expected, the results show a decrease in performance for identical stimuli presented in the multiple-choice task compared to the same stimuli used in the 2AFC task. In particular, the increase of stimulus exposure duration does not have an impact on the performances in the multiple-choice task but clearly improve the accuracy in the 2AFC at low coherence level. Moreover, although several studies on decision-making with multiple-choice tasks have shown that more choices tend to prolong decision-making time, the data do not show a significant increase in reaction time in the multiple-choice task.

In Section 3, we propose a factor that may impact the performance gap in horizontal movements in the multiple-choice task compared to the 2AFC task observed in the previous section. The distribution of performances along the ten directions tested in the multiple-choice task is not homogeneous. Accuracy is significantly better for the directions of horizontal stimuli, which are the only ones tested in the 2AFC task. This result is established both in the multiple-choice task and in a session with 100% coherence. The possibility that participants who started with the 2AFC task needed time to adapt and initially favored these two directions is refuted. Another hypothesis considered is that biomechanical costs may bias movement selection.

Another distinctive point, not yet addressed, between the two protocols is described and analyzed in Section 4. The presence of feedback in the 2AFC task and its absence in the multiple-choice task may lead to faster learning by the participants and thus to better performance.

Finally, in Section 5, we explore an intriguing side effect observed in our participants' behavior during the multiple-choice experiment described in the first section. Our results suggest the presence of a visual illusion within the RDM stimulus. This phenomenon is latent in the 2AFC task, and although it is present, it is not observable under such conditions. The current scientific literature, based primarily on stimuli with two diametrically opposed direction options, does not mention this phenomenon.

Following each of the previously mentioned result sections analyzing our data, there is a discussion linking the implications of our findings with those available and documented in the literature.

We conclude this thesis with a summary of our most pertinent results and an overview of future objectives and challenges in Chapter 5.

Chapter 2

State of the art

2.1 Neural mechanisms and brain regions involved in Decision-Making

In this section, we explore how sensory information influences decisions, particularly within the context of perceptual decision-making tasks. We examine the integration of sensory inputs and their impact on the accuracy and speed of decision-making. To understand these processes, it is essential to analyze the neural pathways and cortical areas involved in processing visual motion information.

Historically, the foundational principles of this process have been studied primarily through 2AFC tasks with saccadic eyes movements. Over the last century, extensive behavioral and neurophysiological data have been gathered from these decision-making task. This body of research highlights specific brain regions that play a role in the still not fully understand neural decision processes.

Visual information captures by the retina reaches the Primary Visual Cortex (V1) through the lateral geniculate nucleus (LGN). Information referring to form and color of the visual stimuli is further processed via the ventral stream, passing through V4 and the inferior temporal (IT) cortex. Information about the spatial localization and the control of action is further processed via the dorsal stream. Since motion information is the key feature in the RDM task discussed here, we will focus on the cortical areas along the dorsal stream, this information is then sent from V1 over the Middle Temporal (MT). [32]

The MT area is the first cortical region downstream from the visual cortex that encodes motion direction information. MT neurons are tuned to specific directions of motion and have direction-sensitive tuning curves. When exposed to an RDM stimulus, MT neurons will increase their firing rates with higher coherence of motion in their preferred direction and decrease firing for motion in the opposite direction. [13] [12] This suggests that the MT area serves as the initial evidence source for

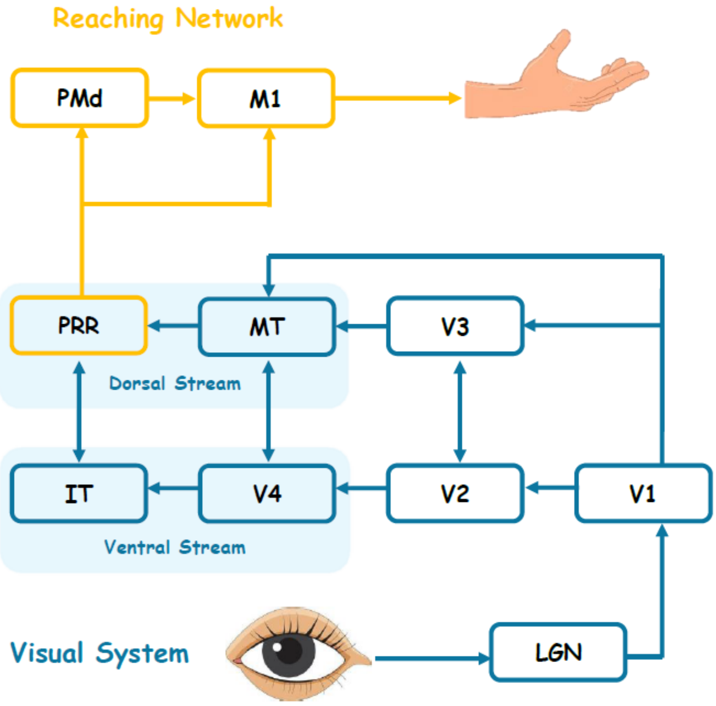

Figure 2.1: **Neural circuitry engaged in perceptual decision-making tasks:** Visual information captures by the retina reaches the V1 through the LGN. Information referring to form and color of the visual stimuli is further processed via the ventral stream, passing through V4 and the IT cortex. Information about the spatial localization and the control of action is further processed via the dorsal stream. This information is then sent from V1 over the MT to the PRR. The PRR projects directly to PMd and M1. The PMd projects, in turn, to M1.[32] [14]

downstream decision-making processes. This was demonstrated by Ditterich et al., who showed that stimulating MT neurons affects decision behavior similarly to providing additional visual evidence.

Beyond the MT area, decision-related activity has been observed in the Orbitofrontal Cortex (OFC), Dorsolateral Prefrontal Cortex (dlPFC), Ventromedial Prefrontal Cortex (vmPFC), and Anterior Cingulate Cortex (ACC). Studies have shown that neural activity in these areas can predict a subject's choice before the execution of a response.

The OFC is involved in updating behavioral responses according to changes in reward rules. It plays a crucial role in evaluating rewards, punishments and adapting behavior to environmental changes.

The ACC is involved in action-reward contingency learning, i.e., the association between an action and its reward. It plays a role in reward expectation and response to stimuli predicting future rewards.

The dlPFC is involved in working memory processes, action planning, and reward processing. It modulates activity based on upcoming rewards and planned actions, as well as processing sensory parameters of visual stimuli and reward predictability.

Similarly, choice-predictive neural modulation has been reported in sensorimotor regions, such as the Superior Colliculus (SC), Lateral Intraparietal (LIP), Posterior Parietal Cortex (PPC), and primary motor and premotor cortices. [28]

LIP neurons, in the PPC are involved in both sensory and motor functions and contribute to forming intentional motor plans. Specifically, LIP neurons become active before a saccade directed toward their "Response Field (RF)" and also respond to visual stimuli within their RF. In RDM tasks where participants used arm movements instead of saccades, similar neural characteristics were observed in other PPC areas, particularly the Parietal Reach Region (PRR). PRR neurons, which are involved in preparing arm movements, exhibit sustained activity during delayed reach-to-target tasks and respond strongly to the appearance of a visual reach target in their RF, similar to LIP neurons during saccades in the same paradigm. The neural activity assumptions and predictions discussed in this section generally apply to both LIP and PRR. [5] [33] Research by Christopoulos et al. (2015) shows that the PRR, plays a crucial role in decision-making processes involving arm movements. By reversibly inactivating the PRR, the study found a significant reduction in contralesional reach choices, without affecting saccade choices. This effector-specific impact underscores the PRR's involvement in reach decisions rather than general spatial attention or awareness. [15].

In our paradigm, which requires indicating the response through a reaching movement, the command to execute the chosen reaching movement is then routed to the movement preparation network. This network includes the dorsal premotor cortex (PMd), the Primary Motor Cortex (M1), and the PRR. These regions play an important role in the sensorimotor transformation of visual and other sensory information to generate arm-reach signals.

Histological studies suggest a topographic organization of the PMd, dividing it into rostral and caudal subregions, each representing different body parts. The PMd is interconnected with the M1, area 5 (within the PRR), the dlPFC, the OFC, and the ACC.

The M1, located anterior to the central sulcus, is interconnected with the PMd and area 5, and its strong projection to the spinal cord underlies its primary role in movement execution. It also weakly projects to the dlPFC.

The PRR includes area 5 of the PPC, mentioned several times above, V6A in the parieto-occipital area, and the Medial Intraparietal Area (MIP) within the intraparietal sulcus.

As part of the movement preparation network, the PMd, M1, area 5, and MIP play distinct roles in planning and executing reaching movements.

In particular, the PMd and M1 have shown that they contain neurons representing multiple aspects associated with potential arm movements, including the likelihood of executing a given movement, the type of movement, direction, amplitude, speed, number of targets present on the stimulus, and expected outcome. A study by Donner et al. (2009) demonstrated that sensory evidence from the MT area was integrated over time in the motor cortex to influence perceptual decisions. They observed a progressive increase in activity, during stimulus observation, in the gamma (64-100 Hz) and beta (12-36 Hz) frequency bands in the motor cortex. This accumulation of activity predicted the subjects' perceptual choices several seconds before they made an observable manual response. The beta frequency band is often associated with motor planning and maintaining a resting state in the motor cortex, while the gamma frequency band is often linked to higher cognitive processes, such as attention and conscious perception. These findings highlight the integral role of frequency-specific neural population activity in the motor cortex as a window into the mechanisms underlying perceptual decisions. [20]

Regarding area 5 and the MIP within the PRR, studies have shown their role in visuomotor transformation, representing information related to action-relevant variables such as the current position of the hand, head, and eyes. [14] [18]

As mentioned several times above, recent research indicates that brain regions traditionally viewed as responsible for planning and executing movements also play a role in processing decision-related information. This challenges the classical model, inherited from cognitive psychology, which separates perceptual, cognitive, and motor systems and is still widely used in theoretical neuroscience to understand behavior from neural data.

In reality, sensory, cognitive, and motor variables are often interwoven in the activity of neurons across various brain regions. This interconnection complicates the interpretation of brain region functions based on traditional distinctions between perception, cognition, and action, and has led to ongoing discussions about the specific roles of these regions. [17]

However, it remains uncertain whether these regions actively participate in the decision-making process or merely reflect evidence integration occurring elsewhere. [28]

2.2 The Evolution of the RDM Paradigm to Multiple-Choice Decision Making

The paradigm which is implemented and is deeply analysed in this thesis is the RDM stimulus. It integrates sensory and motor circuits which are among the most extensively studied systems within neuroscience. Consequently, it's hardly surprising that neuroscientific research on decision-making often focuses on perceptual decisions, particularly those involving sensorimotor processes. The RDM paradigm also incorporates motion detection, one of the oldest and most fundamental forms of vision, as noted by Walls in 1942. This is likely because motion detecting is crucial for survival. For humans, motion captures attention effectively and holds it. [38] For instance, a moving digital advertisement is more likely to catch a shopper's eye and interest for a longer period than a static poster as it triggers peripheral motion detectors.

Developed by Newsome and colleagues in the 1980s, the RDM paradigm presents participants with a visual display of moving dots, where a portion of the dots move coherently in a single direction while the remainder move randomly. This setup allows researchers to manipulate the coherence level of the dot motion, providing a controlled method to study how sensory information influences decision-making processes. Typically, participants are instructed either to wait until the end of the stimulus to indicate their choice by committing to an action or to initiate their movement as soon as they feel confident in their decision. This thesis employs the latter configuration, allowing measurement of Reaction Time (RT) as a variable to evaluate behavioral performance. The RT is intracectively linked with the Decision Time (DT). RT in the RDM task are usually long, on the order of several hundred milliseconds.

The RDM paradigm has naturally extended to more than two alternatives, facilitating studies on the transition from binary to multiple-choice decision-making.

Increasingly, researchers are moving beyond the 2AFC paradigm to explore multiple-choice decision-making, validating theories initially developed for binary choices. There are two main approaches: the first involves increasing the number of discrete targets to more than two, and the second allows for choices along a continuous spectrum, where participants select from a range of options rather than discrete targets.

Numerous studies have adopted the experimental framework that Churchland et al. introduced in 2008. This framework involved macaque monkeys performing a 2AFC RDM task that required saccadic eye movements towards the selected target, extended to include a configuration with four targets separated by 90-degree intervals. This pioneering study was notable for being the first to gather electrophysiological data from a task with more than two decision alternatives. Additionally, it featured a control setup with two targets separated by 90 degrees. This configuration uses a subset of the targets and motion directions in the four targets task to distinguish the impacts of having more alternatives from those of decreasing angular distances between targets [16]. Building on this, Niwa and Ditterich employed a variation using three targets that were randomly positioned at the beginning of each experiment and remained stationary throughout that session. The targets are spaced at 120-degree intervals on an imaginary circle [29]. Similarly, Albantakis et al. used the four-target model developed by Churchland et al., while also exploring different configurations with two targets [7] [6]. In a more

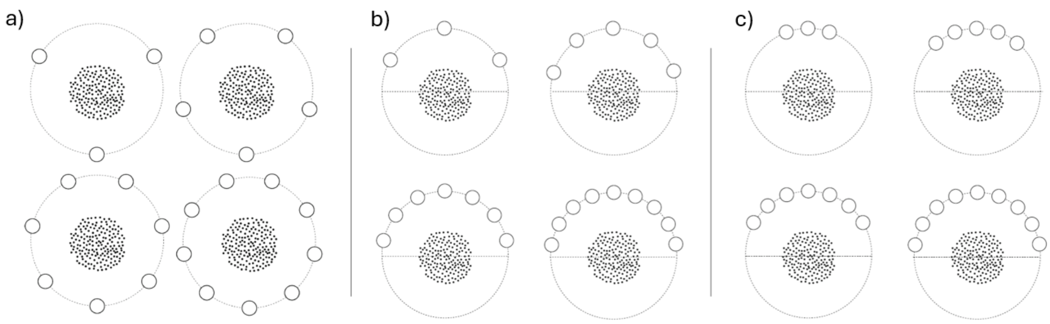

Figure 2.2: **Configurations of alternatives used in a study by van Maanen and al.** **a)** Three, five, seven, and nine targets positioned around a circle to optimize angular separation. **b)** Three, five, seven, and nine alternatives equally spaced on the half circle. **c)** Clustered condition with targets evenly spaced at intervals of $1/9\ \pi$. Note that as the number of alternatives increases, the similarity between two adjacent alternatives increases [34].

recent publication, researchers have investigated how changes in the number of response alternatives in a RDM task affect decision-making. The key complication in applying the RDM paradigm to multiple-choice decision-making is the interaction between the number of alternatives and their similarity. Increasing the number of alternatives reduces the relative angular distance between them, thus increasing their similarity. They examine diverse configurations where three, five, seven, or nine targets were positioned around a circle to optimize angular separation (Figure 2.2 a). They used odd numbers of alternatives to ensure that two alternatives were never diametrically opposed. Further experiments tested layouts with options maximally spread across half a circle (Figure 2.2 b) and a clustered format where targets were evenly spaced at intervals of 1/9 π (Figure 2.2 c). Such varied configurations are instrumental in analyzing how the number and spacing of choices affect the precision and speed of decision-making. [34]

Another approach to extending the RDM paradigm, though less explored, involves making the decision space continuous. Beck et al. in 2008 implemented this by requiring observers to indicate the direction of motion along a continuous circle. This setup reflects more naturalistic decision-making situations where choices aren't limited to binary outcomes but can involve selecting from many potential actions. [10]

Chapter 3

Materials and methods

3.1 Participants

A total of 24 right-handed participants (13 females) ranging in age from 18 to 25 years old were recruited for this study and were enrolled in the two experiments, five of them performed as pilot participants. One subject is an author on this paper and the others participants were naive to the purpose of the study. All subjects had normal or corrected vision, and had no known neurological disorder or any motor disabilities. Participants provided their written informed consent before the experiment and agreed that the results could be published anonymously.

3.2 Experimental paradigm

3.2.1 Set-up

Participants engaged in experiments at the Institute of Neuroscience of UCLouvain, Belgium, using the Kinarm end-point robotic device (KINARM). This device, developed by BKIN Technologies Ltd, Kingston, Canada, is officially known as the Kinesiological Instrument for Normal and Altered Reaching Movements and is depicted on Figure 3.1. In the setup, participants sat in an adjustable chair and gripped the handle of the right robotic arm with their right hand, which enabled movement within a horizontal plane.

To ensure focus on the task, the direct view of both the participant's hand and the robotic arm was obstructed. However, participants interacted with virtual cursors displayed on a screen, represented by a visible white dot with a 0.5-cm radius aligned to the position of the right handle. They maintained a posture where their arm was vertically aligned at rest, with the elbow bent at a 90° angle. Stability was further ensured by a head-bar that fixed the distance between the

Figure 3.1: **Kinarm end-point robotic device:** Experimental setup used to collect behavioral data. Participants sat in an adjustable chair and gripped the handle of the robotic arm with their right hand. The device acquires the X and Y positions of the handle in real-time.

participants' eyes and the monitor.

The system's computer, operating at a frequency of 1kHz, precisely recorded the position and speed of the handle, facilitating accurate real-time data collection and analysis.

3.2.2 Protocol Description

The experimental protocol was structured around two distinct tasks, inspired by methodologies previously developed by Churchland et al. and adapted for use with the KINARM system. The control of the behavioural task, the display of the stimulus and the synchronisation of task events were carried out using several programming environments: Simulink, MATLAB and the software supplied with the KINARM robot called Dexterit-E. The code for the RDM stimulus paradigm is based on a sample task available in the library on the KINARM website and adapted to match our protocol.

3.2.3 Task 1: Two-Alternative Forced Choice

In this task, participants are initially presented with a blue Start circle. Once the cursor is positioned in this circle, small dots appear, uniformly distributed within a 10 cm diameter aperture. A subset of these dots move coherently toward one of two horizontal directions, while the remainder move in random directions. After a predetermined duration (0.5, 1, or 2 seconds, depending on the trial), two arrow targets positioned at angles of 0 and Π radians on a circular display appear. Participants indicate their perceived direction of motion using the right handle of

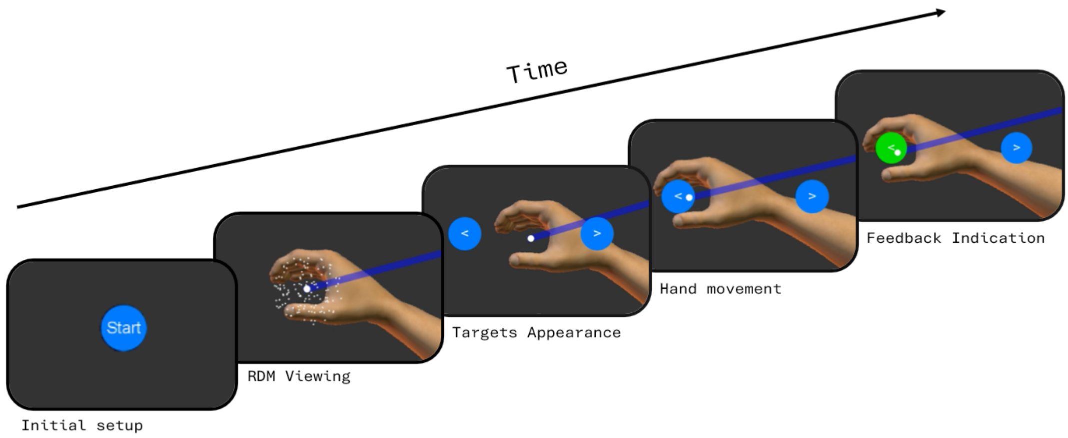

Figure 3.2: **Experimental design:** 2AFC RDM paradigm with manual indication of choice. To start a trial, the subject has to be at the starting position (blue Start button). Then, the RDM stimulus appears on the screen. The visual arrow targets show up on the screen once the motion stimulus switches off. The participant indicates his choice by moving toward one of the targets, the trajectory is recorded. Feedback is given by the colored target.

the KINARM device by aligning a cursor with one of the two targets. Real-time feedback is provided through color coding: selecting the correct target turns the cursor green, whereas selecting an incorrect target turns it red.

3.2.4 Task 2: Multiple Direction Choice

The second task mirrors the first in terms of visual stimuli but features ten net stimulus directions equally spaced around the circle, each separated by an angular distance of $\pi/5$ radians. A key element is that participants are not informed that there are only ten directions; they are told that the dots could move coherently across the entire circle, from 0 to 360 degrees. Unlike in the 2AFC task, no target appears once the small dots disappear. Participants are tasked with executing straightforward trajectories in the direction of the majority of the dots and are instructed to exit the circle. Unlike the first task, no feedback is provided during this task.

The adjustment in the number and arrangement of net stimulus directions in our RDM stimulus was driven by specific observations during initial pilot sessions. Originally set to the eight cardinal points, the directions showed significant variability in participant accuracy. Data from five participants in the pilot trials revealed that diagonal movements resulted in higher variance in performance

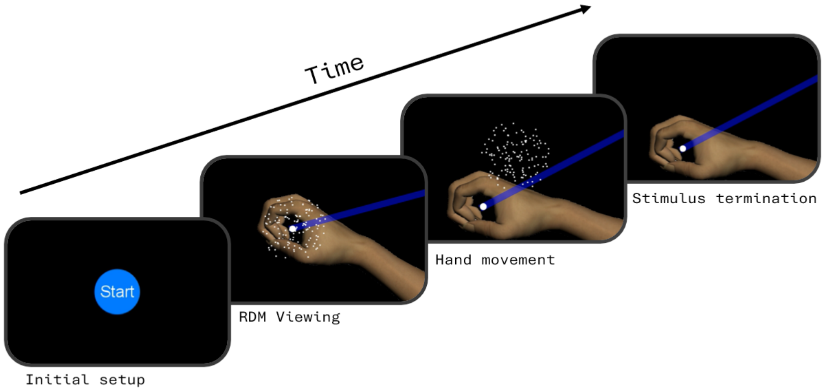

Figure 3.3: **Experimental design:** The multiple-choice RDM task with manual indication of choice. To start a trial, the subject has to be at the starting position (blue Start button). Then, the RDM stimulus appears on the screen. The participant indicates his choice by moving in a straight line to exist the circle aperture, the trajectory is recorded. No feedback is provided during this task.

compared to the four cardinal points, suggesting that an eight-target setup did not provide a balanced assessment of response ability. To achieve a more uniform distribution of difficulty and reduce data heterogeneity, we decided to increase the number of targets to ten. This change is intended to optimize the equidistance of targets around the central aperture, thus reducing the predominance of cardinal orientations and allowing for a more uniform comparison of performance across different directions. The exact positions of the ten targets are chosen to retain the horizontal targets (0 and 180 degrees) to enable direct comparison with the 2AFC task. The impact of target positioning is analyzed in a later section.

3.2.5 Experimental Parameters and Setup of the RDM stimulus

Both tasks employ varying levels of dot coherence (10%, 20%, and 30%) and duration (0.5, 1, or 2 seconds) to modulate task difficulty. The five pilot participants indicated that these coherence levels made the task sufficiently demanding for our participants, especially in the case of multiple targets. Dot positions are uniformly distributed within a 10 cm diameter aperture. If any of the signal dots are to move out of the circular aperture, they are wrapped around to appear from the opposite side to conserve dot density. Participants are instructed to respond as swiftly and accurately as possible.

3.2.6 Session Structure

All subjects participate in two experimental sessions, one for each task condition. The session associated with the 2AFC task includes 6 trials with a coherence level of 80% which served to familiarize them with the procedure. Prior to the multiple-choice experimental session, each participant engages in at least one training session of approximately ten trials with coherence level of 80% to ensure they understand how to indicate the motion direction and stabilize performance levels.

The multiple-choice task is divided into five blocks, each comprising 180 trials, totaling 900 trials. Participants are allowed brief rest periods between blocks. Conversely, the 2AFC task consists of a single block of 180 trials.

At the end of the multiple-choice task, participants are asked to perform 20 movements at 100% coherence, executing two movements per target, thereby revealing the ten directions to delineate clear pattern trajectories. This session is referred as 'Feedback' task.

To control for potential sequencing effects and variability in task performance, the order of conditions and trials is uniquely randomized for each participant. The order of starting with Task 1 or Task 2 is also randomized for each subject.

3.3 Data collection

Data from the KINARM machine are saved as .KINARM files. To analyze these files, they are converted into MATLAB structures, then to CSV files, and finally store in a pandas dataframe in Python.

Each row of the dataframe represents a trial and includes details such as participant number, trial number, coherence level, stimulus duration, x and y hand positions, the time in milliseconds when the stimulus appears on the screen, the direction of the moving dots, and the session of the trial. Additional data such as error angle, speed vector of the trajectory, an accuracy measure, and the time the participant decides to start his movement are also calculated and added to this dataframe. These variables are explained further in this section.

The task is coded so that a trial ends when the participant moves more than 10 cm from the center of the stimulus and the dots are turned off. This means that the end of a decision-making trajectory that starts after the dots turn off will appear in the next trial.

The speed is computed at each time step using the Pythagorean theorem to combine the horizontal and vertical components of velocity. The formula for speed $v[k]$ at the k-th time step is given by:

$$v[k] = \sqrt{(v_x[k])^2 + (v_y[k])^2} \tag{3.1}$$

with $v_x[k]$ and $v_y[k]$ are the velocities in the x and y directions, respectively.

To calculate the error angle, several steps are necessary. First, it is essential to determine the exact position when the participant exits the 10 cm stimulus aperture. To do this, we check that the trajectory enters the start section (as mentioned above, the trial starts with the end trajectory of the previous trial) and identify the first occurrence where the distance to the center is 10 cm. This occurrence is referred to as the 'reference position'. Not every trial starts at the exact same position due to the 3 cm radius of the start button. For this purpose, two methods are implemented to determine the chosen direction.

The first method involves selecting time steps judiciously before and after this reference position on the hand displacement vectors along the x-axis and y-axis. The slope of the linear regression line through these two displacement vectors can be calculated using the least squares method. This involves finding the slope m such that:

$$m = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2}$$

where n is the number of data points, and x and y are the vectors containing the positions of the hand on the x and y axes, respectively.

The second method also uses linear regression but, instead of fitting it to the trajectory of the hand, it takes only two points: the reference position and the center of the stimulus. The components of the vector are then slightly adjusted according to the direction of the trajectory. The direction on the x-axis is given by the sign of the difference between the last and the first value of x:

$$\text{direction}_x = \begin{cases} 1 & \text{if } (x_n - x_1) > 0 \\ 0 & \text{if } (x_n - x_1) = 0 \\ -1 & \text{if } (x_n - x_1) < 0 \end{cases}$$

The final direction vector obtained as the participant's response can be defined as follows:

$$\vec{r} = [\text{direction}_x, \text{direction}_x \cdot m]$$

where m is the slope calculated previously.

By calculating the arccosine of the dot product and the norm of the response vector and the vector of the net direction of the stimulus, the angle formed by the two vectors is computed. This angle is referred to as the 'error angle' and is added directly to the dataframe. This error angle is always between 0 and 180 degrees due to the domain of the arccosine.

$$\theta = \arccos\left(\frac{\vec{r} \cdot \vec{s}}{\|\vec{r}\|\|\vec{s}\|}\right)$$

where $\vec{r}$ is the response vector and $\vec{s}$ is the vector of the net direction of the stimulus. It should be noted that the two methods described previously do not yield significantly different results in the calculated error angle.

A second measure to evaluate participants' performance in estimating the trajectory of the stimulus is referred to as 'Accuracy' and is used in the article "What a difference a parameter makes: A psychophysical comparison of RDM algorithms" [30]. The accuracy measure is a percentage ratio, calculated as follows:

$$\text{Accuracy Measure} = 100\text{x}\left(1 - \frac{|\theta|}{90°}\right) \tag{3.2}$$

Here, θ is the absolute error between the subject's estimated motion direction and the actual direction as explained in the above paragraph. This formula translates the error in degrees into a percentage, where 0% represents the worst performance (an error of 90°) and 100% represents perfect performance (no error). An error of 90° implies guessing, as it represents the maximal orthogonal deviation from the correct direction. Thus, this scale effectively differentiates between random guessing and accurate perception. The use of a percentage scale simplifies reporting and statistical analysis, allowing ones to focus on percentage improvements or decrements. This method of quantifying accuracy is versatile and can be uniformly applied across different experimental designs and research settings, making it valuable for compiling and comparing results across studies.

In our analysis of response data to the RDM stimulus, one of the most crucial measures is the RT of participants. RT is defined as the interval between the appearance of the stimulus and the moment when the participant initiates a movement in response to the stimulus, essential for assessing the speed and accuracy of the sensorimotor response. The metric is calculated from raw data by taking the first moment when the movement speed exceeds a threshold of 0.05 m/s. This threshold is set to reflect an intentional movement in response to the dots, rather than random variations or minor movements. The threshold is assumed as independent of motion coherence and of the number of targets in the stimulus paradigm. The sampling rate, indicating the number of measurements per second, allows us to convert the temporal index into an accurate RT. By this approach, we can isolate the reactive action of participants. This measure is added to the dataframe as a new column, enriching our dataset with a key piece of behavioral analysis information. However, for some trials, the RT is defined as -1. This occurs in cases where, for a given trial, no data point exceeds the defined speed threshold after the appearance of the stimulus. In a normal trial, there are two speed peaks: the first to return to the start, and the second to indicate the direction of the points (Figure 5.2 in Appendix). However, some trials have a speed peak to return to the Start and do not stop there but directly initiate their decision-making movement with a speed that continues to decrease as shown in Figure 5.1 available in Appendix.

3.4 Statistical tools

In the subsequent sections, various statistical tests are conducted. The tests and measures used in this thesis are defined here as well as the specific assumptions they rely on. Note that, the scale of the measurement of the collected data is continuous and we make the hypothesis that participants represent a randomly selected portion of the population.

3.4.1 Shapiro-Wilk test

In statistics, the Shapiro-Wilk test assesses the null hypothesis that a sample is drawn from a population with a probability distribution curve with the highest frequency of occurrence at the center, and the frequency decreases with distance from the center. A p-value greater than 0.05 indicates that the data can be considered to come from a normal distribution. According to the normality of the data, a parametric method or a nonparametric method will be needed.

The Shapiro-Wilk test statistic is calculated as follows [1]:

$$W = \frac{(\sum_{i=1}^{n} a_i x(i))^2}{\sum_{i=1}^{n}(x(i) - \bar{x})^2}$$

with:

- n is the sample size,
- $x(i)$ is the i-th order statistic (sorted value) from the sample,
- $\bar{x}$ is the sample mean,
- a_i are constants computed based on the expected values of the order statistics under the null hypothesis.

3.4.2 Levene Test

To assess the homoscedasticity of variances between two groups, the Levene test is used. This test evaluates whether the variances of samples from populations with equal means are statistically similar. If the p-value is lower than a defined threshold the homogeneity of variances condition is not verified.

The Levene test statistic is calculated as follows [11]:

$$W = \frac{(N-k)(k-1) \cdot \sum_{i=1}^{k} N_i (z_i - \bar{z})^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (z_{ij} - \bar{z}_i)^2}$$

with:

- N is the total number of observations,
- k is the number of groups,
- N_i is the number of observations in the i-th group,
- $\bar{z}_i$ is the mean of the observations in the i-th group,
- $\bar{z}$ is the overall mean,
- z_{ij} is the j-th observation in the i-th group.

3.4.3 Mixed Effect Models

A mixed effects model is a statistical model that includes both fixed effects and random effects. These models are particularly useful due to their flexibility in handling missing values, accounting for non-constant variance over time, and accommodating repeated measurements on the same participants [25].

$$y_i = (\alpha + \eta_{j[i]}) + X_i \beta + \epsilon_i \tag{3.3}$$

$$\epsilon_i \sim \mathcal{N}(0, \sigma_y^2) \tag{3.4}$$

$$\eta_j \sim \mathcal{N}(0, \sigma_\alpha^2) \tag{3.5}$$

with:

- y_i: The dependent variable for trial i.
- α: The intercept.
- $\eta_{j[i]}$: The random effect specific to each participant j to which trial i belongs.
- X_i: The explanatory variables.
- β: The fixed coefficients.
- ϵ_i: The residual error term for trial i, capturing the variations not explained by the fixed and random effects.

In this thesis, random effects is based on participants, and fixed effects often include the level of stimulus coherence and the duration of exposure to the stimulus. For certain analyses, other fixed effects such as task type and session number may also be used. Although coherence level and stimulus duration could be interpreted as random effects to generalize the conclusions to all levels of coherence and duration, when the number of levels of a random factor is low, it is generally not possible to estimate the variance of this effect reliably. Therefore, we have preferred to treat the level of stimulus coherence and the duration of exposure to the stimulus as fixed factors since both contain only three levels.

It is also possible to estimate a "random slope model" where both the intercept and the slope can vary by participant:

$$y_i = \alpha_{j[i]} + \beta_{j[i]} x_{1i} + \epsilon_i \tag{3.6}$$

$$\epsilon_i \sim \mathcal{N}(0, \sigma_y^2) \tag{3.7}$$

$$\alpha_j \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2) \tag{3.8}$$

$$\beta_j \sim \mathcal{N}(\mu_\beta, \sigma_\beta^2) \tag{3.9}$$

In the random slope model (Equation 3.6), both the intercept $\alpha_{j[i]}$ and the slope $\beta_{j[i]}$ can vary by participant. This means that each participant j can have its own unique intercept and slope.

The choice to include a random slope can depend on several factors. Firstly, visual exploratory analysis of the data can help determine if the slope varies from group to group, suggesting the need for a random slope. Secondly, the amount of available data plays a significant role. More random slopes with potential correlations require a larger quantity of high-quality data for accurate estimation. Lastly, the objective of the study and the ease of interpreting a more complex model also influence the decision to include a random slope.

Mixed models achieve better estimates of slopes and intercepts by estimating a value between two extremes cases. The case where a single slope and intercept are estimated for all the data, ignoring group effects. The case where a separate line is estimated for each group [25].

Model application conditions

The residuals must be independent of each other. This means that the error of one observation should not influence the error of another observation.

The residuals must have a constant variance across different values of the predictors. This homoscedasticity assumption is essential to ensure the efficiency and validity of the coefficient estimates in the model.

The residuals should follow a normal distribution [25].

These conditions are typically verified using aforementioned diagnostic tests.

Limitations of the model

One of the problems with the mixed effect model is that the estimates of slopes and intercepts can be very poor, especially for groups with limited data. However with our data, as long as the session variable is not added as a fixed effect, each participant has performed 10 times the same trial with the same parameter combination, ensuring a more robust estimation. Other issues to consider include the presence of outliers, which can significantly influence the model's estimates and potentially lead to biased results. Multicollinearity is another concern, as the explanatory variables should be independent of each other. High multicollinearity can make it difficult to determine the individual effect of each predictor and can inflate the variance of coefficient estimates. Additionally, overfitting can occur when there are too many parameters relative to the number of observations, causing the model to become overly complex and fit the noise in the data rather than the underlying relationship [25].

3.4.4 Permutation test

Permutation test is a non-parametric statistical method used to determine the significance of observed data without making assumptions about the underlying distribution. The null hypothesis is that all samples come from the same distribution. Under the null hypothesis, the distribution of the test statistic is obtained by calculating all possible values of the test statistic under possible rearrangements of the observed data. Practically, the data labels are randomly shuffle to create new datasets under the null hypothesis. This involves reassigning the data points to different groups while maintaining the original data values. This process is repeated many times, 10000 iterations are performed. The p-value is calculated as the proportion of permuted test statistics that are as extreme as or more extreme than the observed test statistic. If the p-value is below a predefined threshold, the null hypothesis is rejected, indicating that the observed effect is statistically significant [2].

3.4.5 Wilcoxon Signed-Rank Test

The Wilcoxon Signed-Rank Test is a non-parametric statistical test used to compare two related samples to assess whether their population mean ranks differ. It is the non-parametric alternative to the paired t-test and does not assume normality of the data. The null hypothesis is that the median difference between the pairs of observations is zero. The test is based on the ranks of the differences between pairs of observations to determine the p-value. If the p-value is less than the significance level, the null hypothesis is rejected, indicating that there is a significant difference between the pairs [3].

3.4.6 Kruskal-Wallis Test

The Kruskal-Wallis Test is a non-parametric statistical test used to compare three or more independent samples to determine whether there are statistically significant differences between their population medians. It is the non-parametric alternative to the one-way ANOVA and does not assume normality or homogeneity of variances in the data.

The null hypothesis for the Kruskal-Wallis Test is that the samples come from populations with the same median. The test works by ranking all data points from all groups together, then comparing the sum of ranks between groups.

If the p-value derived from the test statistic is less than the chosen significance level, the null hypothesis is rejected, indicating that there is a significant difference between the groups [4].

Chapter 4

Results

4.1 Investigating performance under varying levels of task complexity

In this section, we explore decision-making tasks involving multiple choices, with a focus on continuous decision space. It remains uncertain at which point participants are unable to differentiate between potential motion directions, or how precisely they can identify the direction of motion in continuous tasks. To enhance our understanding of the complex mechanisms behind the cognitive processes of perceptual decision-making, the relevant observations from behavioral data collected during the experiment is analysed. These data can later be used to validate —or invalidate— models designed based on 2AFC experiment.

The accuracy, the error of angle and the RT are calculated as previously described in the section 3.3. The effects of coherence level and stimulus duration on participant performance in the multiple-choice task are investigated. The hypothesis is that performance improves with higher coherence levels or longer duration levels. The longer the stimulus is visible to the participant, the more evidence can be gathered, leading to more accurate choices. An internal decision criterion determines when the decision process ends and triggers the corresponding motor response, referred to as RT. Some trials had to be excluded because they failed to reach a decision within the window of 3,000 ms.

The graph shown on Figure 4.1 compares the performance of participants across the three levels of coherence for the three stimulus duration levels. Here, the performance criterion is the mean accuracy, where an accuracy close to 100% indicates minimal error. For each stimulus duration, the accuracy globally increases with the coherence level, as expected. For the 2000 ms duration, and to a lesser extent for the 1000 ms duration, there appears to be a ceiling effect at higher

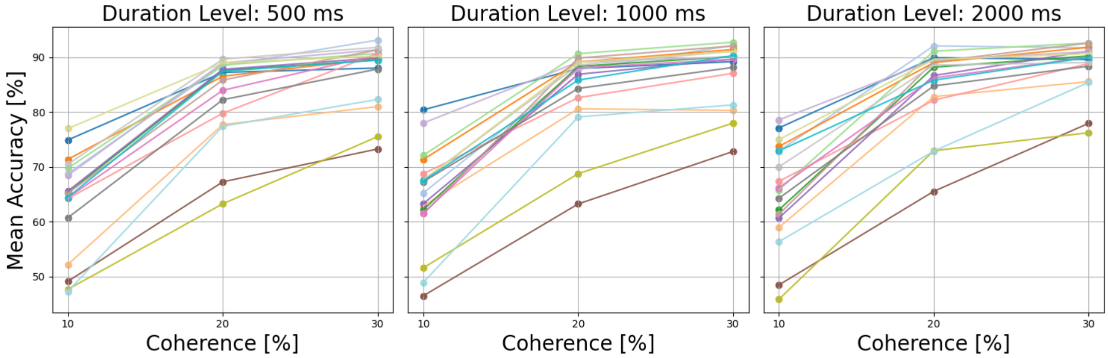

Figure 4.1: **Comparison of participant performance across levels of coherence:** The graph compares the mean accuracy of participants across three levels of coherence for three different stimulus durations (500 ms, 1000 ms, and 2000 ms). Higher accuracy indicates minimal error. For each stimulus duration, accuracy increases with coherence level. Variability in accuracy among participants is evident.

coherence levels, where the improvement in accuracy does not increase as sharply as it does between coherence levels of 10 to 20%. The accuracy at a coherence level of 20% is already very high, so it cannot improve significantly further. There is notable variability in accuracy among participants. Some participants appear to consistently perform worse across all coherence levels and stimulus duration, this is the case for the brown and mustard lines.

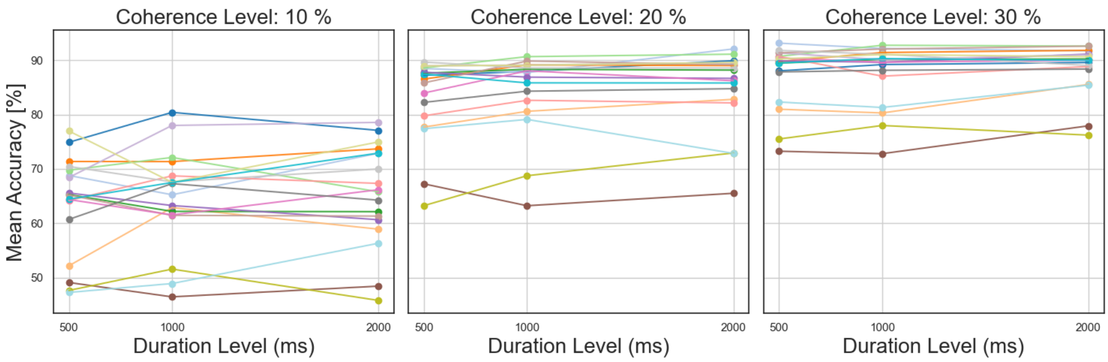

Figure 4.2: **Comparison of participant performance across stimulus durations:** The graph compares the mean accuracy of participants across three stimulus durations for three different coherence levels. Higher accuracy indicates minimal error. The variation of accuracy among participants decreases with coherence level. At all coherence levels, there is no consistent trend indicating that longer duration always leads to better performance.

The mean accuracy of participants as a function of the stimulus duration is depicted in the graph on Figure 4.2. At the lowest coherence level, accuracy varies widely among participants and shows different trends as duration increases. Some participants improve, while others show little change or even decreased performance. With a moderate level of coherence, most participants' accuracy appears stable across different durations. At the highest coherence level, accuracy is generally higher and more consistent across participants. Most lines are flat or show minor improvements, suggesting that when the signal is coherent, participants can achieve high accuracy regardless of stimulus duration. At all coherence levels, there is no consistent trend indicating that longer duration always leads to better performance.

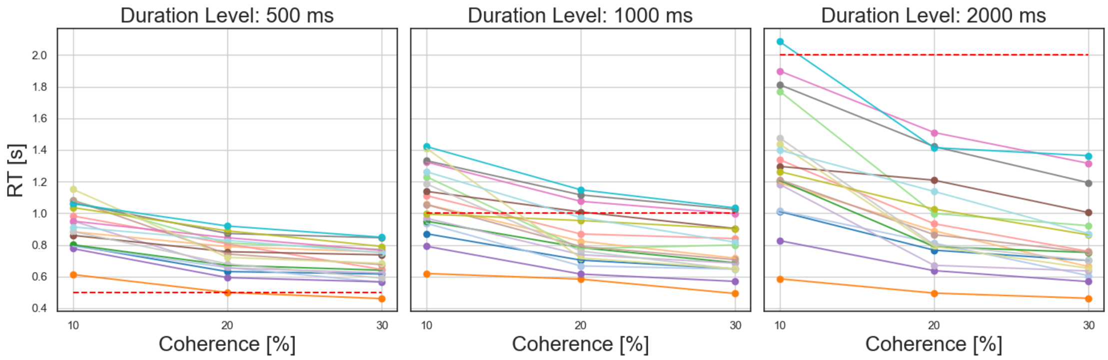

Figure 4.3: **Comparison of participants' mean RT across coherence levels:** The termination of the stimulus is represented by the red dashed line. The mean RT decreases as the coherence of the stimulus increases, suggesting that participants tend to make faster decisions when the motion signal is more coherent. RT increases with longer exposure to the stimulus, suggesting that many participants might be waiting for the stimulus to conclude before initiating their movements.

The graph on Figure 4.3 illustrates the variations in decision-making speed relative to the coherence of the motion stimulus. It clearly shows an inverse relationship between mean RT and coherence levels across three different duration settings. Across all three duration levels, there is a noticeable decrease in mean RT as the coherence of the stimulus increases, suggesting that participants tend to make faster decisions when the motion signal is clearer.

While most participants follow the general trend of decreased RT with increased coherence, the rates of decrease vary significantly among individuals. This variability highlights that while the motion signal's clarity generally aids quicker decision-making, individual differences in processing speed and strategy can influence the extent of this effect.

As expected, the RT increases with longer exposure to the stimulus, suggesting that many participants might be waiting for the stimulus to conclude before initiating their movements. However, this behavior also varies widely among participants, especially at longer duration. For example, the participant represented by the orange line consistently shows RT around 500 ms, regardless of the duration level. In contrast, the participant represented by the bright blue line appears to delay decision-making until the end of the trial, indicating a strategy of maximizing information gathering before committing to a decision.

This pattern of responses broadens at higher stimulus duration, reflecting a greater variance in how participants manage the trade-off between speed and accuracy. The fact that higher coherence not only improves accuracy but also reduces RT supports the idea that more robust sensory input facilitates more efficient decision-making.

The previously analysed figures suggest significant variability in accuracy among participants, which is illustrated by the Figure 5.3 available in Appendix. In that graph, it is evident that four participants (represented by the red, gray, light blue, and grey markers) consistently exhibit lower performance levels compared to their peers across various coherence and duration settings. This pattern suggests significant variability in accuracy among participants. In contrast, the remaining participants display relatively uniform performance, indicating similar levels of behavioral effectiveness in the tasks presented. This distinction underscores the importance of considering individual differences when assessing the efficacy of perceptual decision-making tasks. Moreover, there is more variability in performance for certain combinations of coherence and duration especially with a coherence of 10% some participants have very large error bars, indicating inconsistency in their ability to estimate the direction of the dots. Participants' performances vary less at a coherence of 30%, suggesting that higher coherence stimuli are more easily and uniformly understood by participants, regardless of the stimulus duration.

Two linear mixed models are calculated using the data collected from the multiple-choice task. The first model uses the mean RT as the dependent variable, and the second model uses the mean error angle. The coherence levels and duration levels are included as fixed effects in both models. Due to the results shown in Figure 5.3 and in order to assess individual differences, each subject is included as a random effect. The specification of the first model is as follows:

$$\text{RT}_i = \alpha + \beta_1 \cdot \text{Coherence}_i + \beta_2 \cdot \text{Duration}_i + \eta_{j[i]} + \epsilon_i$$

In the first model, the significant coefficient for the coherence level is -1.804, implying that higher coherence slightly decreases RT. The coefficient for the duration

	Coef.	Std.Err.	z	P>|z|
Intercept	1.077	0.046	23.647	0.000 ***
Coherence	-1.804	0.048	-37.305	0.000 ***
Duration	0.000	0.000	25.827	0.000 ***
Group Var	0.034	0.024		

Table 4.1: Summary of the mixed effects model results with the mean RT as the dependent variable.

level is close to zero, indicating no significant effect of stimulus exposure duration on RT. The variance among participants is negligible, with a coefficient of 0.034 (Table 4.1).

Here is the specification for the second model:

$$\text{ErrorAngle}_i = \alpha + \beta_1 \cdot \text{Coherence}_i + \beta_2 \cdot \text{Duration}_i + \eta_{j[i]} + \epsilon_i$$

	Coef.	Std.Err.	z	P>|z|
Intercept	51.415	2.202	23.350	0.000 ***
Coherence	-136.257	3.235	-42.120	0.000 ***
Duration_Level	-0.001	0.000	-3.039	0.002 **
Group Var	74.089	0.768		

Table 4.2: Summary of the mixed effects model results with the mean error angle as the dependent variable.

In the second model, the significant coefficient for the coherence level is -136.257, suggesting that higher coherence results in a lower mean error angle. For the duration, there is no association with the error angle, as the coefficient is -0.001. The variance among participants is quite high, with a coefficient of 74.1, indicating that a linear mixed model is necessary in this case (Table 4.2).

4.2 Comparative analysis of behavioral data in Multiple-Choice versus 2AFC tasks

In this section of the thesis, the reasoning will be focus on revealing how does instructions such as the number of targets could influence the performance on similar perceptual stimulus task. Traditional 2AFC tasks do not capture some important aspects of real-life decision-making. Usually, in everyday life, we have to choose from more than just two options. This section aims to investigate the brain processes involved in making decisions beyond the simple 2AFC tasks. All the stimuli presented in the 2AFC task are part of the multiple-choice task, specifically, the stimuli associated with targets numbered 1 and 6 in the multiple-choice task (horizontal ones) are identical to those in the 2AFC (Figure 4.11C). We expect the multiple-choice task to be less accurate than binary decisions, especially in the low coherence level. Moreover, several studies on decision-making with multiple-choice task have shown that more choices tend to prolong the decision-making time, leading us to expect longer RT in the multiple-choice task [31].

The results presented in this section aim to compare the behavioral data from the 2AFC task with the corresponding trials in the multiple-choice task. Specifically, only trials associated with the horizontal targets are considered, excluding the rest of the multiple-choice dataset for this part of the thesis. This approach ensures a focused comparison between the two task conditions.

The Figure 4.4 showcases the distribution of RT across the two experimental conditions differentiated by coherence levels and stimulus durations. The duration of the stimulus exposure is written in the title and is also marked by red arrows in each plot for visual reference and quicker interpretation of the histograms. The guidelines for both tasks explicitly instruct participants to begin their movement as soon as they discern the correct net motion of the stimulus and do not require waiting for the stimulus to switch off before committing.

In the 2AFC task, the graph visually captures a significant behavioral trend in response strategies. A pronounced peak in RT systematically occurs just after the duration level no matter the coherence level. This peak indicates that many participants likely deferred their decision until the directional arrows targets appeared at the end of the stimulus duration. The arrows indicate the clear direction (either left or right) of the net stimulus, providing an explicit cue for decision-making. The decision-making process in this context is heavily influenced by the appearance of these arrows targets.

However, the plots also reveal a lower peak, suggesting that the 2AFC RT function might be bimodal. This lower peak, appearing around 500 ms, is presumed

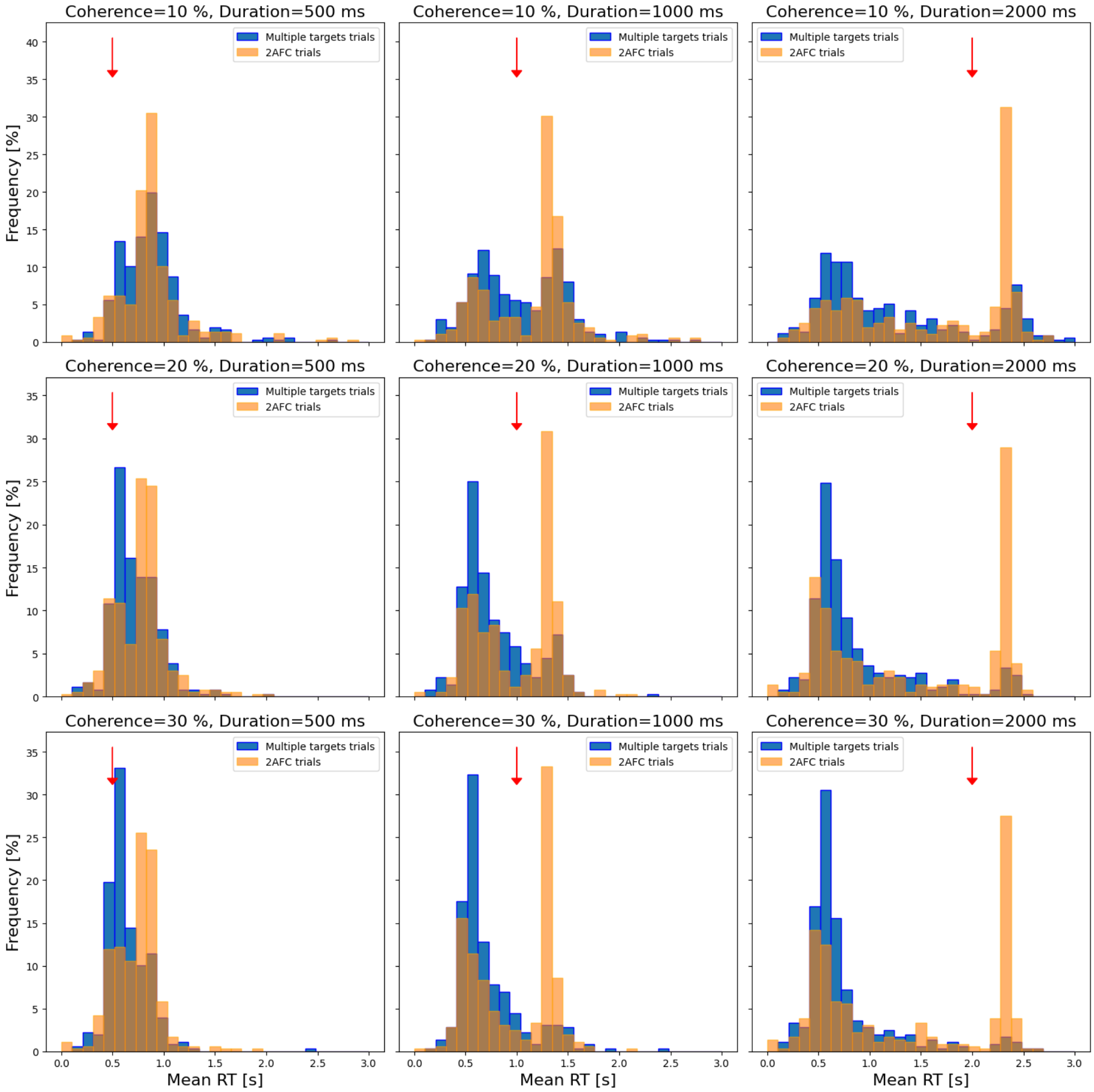

Figure 4.4: **Comparison of the distribution of RT across the two experimental conditions:** In the 2AFC task, a pronounced peak in RT systematically occurs just after the duration level no matter the coherence level and a lower peak appears around 500 ms, suggesting that the 2AFC RT function might be bimodal. The lower peak is presumed to be more associated with the processing of sensory information whereas the higher peak responds to reliance on visual arrows targets. In the multiple-choice scenario, RT generally cluster around 500 ms regardless of the stimulus duration or coherence level.

to be more associated with the processing of sensory information rather than responding to explicit cues. This indicates a dual aspect of the decision-making process within the task, where some participants may rely more on immediate sensory input, while others wait for explicit directional guidance before making a decision.

Conversely, in the multiple-choice scenario, RT generally cluster around 500 ms regardless of the stimulus duration or coherence level. This indicates that participants in multiple-choice tasks are making their decisions based on the stimulus itself without waiting for any additional cues. The consistency of RT around 500 ms across various settings implies a more active engagement with the stimulus and reliance on sensory information processing to make a decision.

The presence of directional arrows in the 2AFC task fundamentally alters the nature of the decision-making process, making it less about sensory processing and more about responding to explicit cues. This could mean that any significant differences in RT between the two tasks do not necessarily reflect differences in sensory information processing capabilities. The longer RT in the 2AFC task reflect a strategic waiting, which differs from the immediate decision-making observed in the multiple-choice tasks where no such cues are provided. Thus, comparing RT across these tasks may not provide a fair assessment of sensory processing capabilities. A considerable improvement for future experiments in the coding of the stimulus paradigm is to eliminate the directional arrow targets that appear at the end of the stimulus. This change ensures the decision-making process reflects genuine sensory information processing, avoiding strategic waiting and reliance on explicit cues.

To address the inconsistency in directly comparing RT between the 2AFC and multiple-choice tasks, the dataset for the 2AFC is truncated to include only trials where the RT occurs before the end of the perceptual stimulus. Originally comprising 3240 trials, the 2AFC dataset now includes 1428 trials. This adjustment aims to retain the lower peak, thereby facilitating a more accurate comparison focused on sensory processing times. For thoroughness, the multiple-choice task dataset is also truncated in the same manner.

The mean RT across the two experimental conditions is represented on Figure 4.5. At a duration level of 500 ms, RT for the multiple-choice task and 2AFC task are similar, with the 2AFC task showing slightly lower RT. For the 1000 ms duration, RT remains consistent across coherence levels for both tasks and are approximately equal. At 2000 ms, there is greater variability, with RT generally longer and more variable for the 2AFC task compared to the multiple-choice task, indicating a reliance on different decision-making strategies as stimulus duration increases.

The histogram displayed in Figure 4.6 illustrates the distribution of mean error angle in both the multiple targets and 2AFC tasks across three coherence levels and

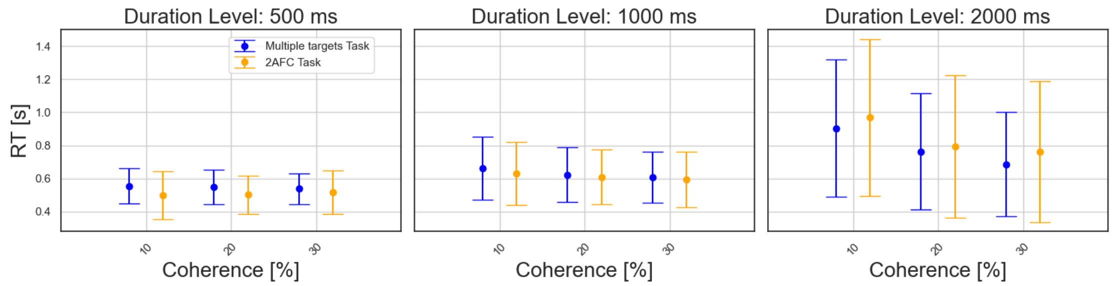

Figure 4.5: **Comparison of the mean RT across the two experimental conditions:** The RT is relatively similar in the 2AFC and in the multiple-choice task with no significant difference.

stimulus duration. Both tasks generally show a concentrated distribution of error angles near lower values, which implies that participant's performance are quite good. The distributions in the 2AFC task are noticeably narrower compared to the multiple targets task, suggesting more consistent accuracy among participants in the 2AFC task likely due to the limited choice set. In contrast, the wider distributions in the multiple targets task could indicate a more complex decision-making process, where participants may be weighing multiple possibilities or experiencing greater uncertainty.

Moreover, the distributions in both the 2AFC task and the multiple-choice task, particularly at lower coherence levels, appear to be bimodal. In the 2AFC task, this phenomenon is expected as there are only two possible directions: the correct one and the direct opposite, which is incorrect. However, for the multiple-choice task, it is surprising that incorrect estimations of the net direction of the stimulus are primarily in the direct opposite direction. Angular Errors were expected to be evenly distributed across all possible responses, i.e., 180 degrees.

This observation suggests that participants accurately extract the correct axis of the stimulus movement but are unsure whether the dots are moving forward or backward. This preliminary finding will be analyzed in detail in Section 4.5 to better understand the possible underlying reasons.

Additionally, a potential link between RT and the mean error angle is investigated. According to Figure 4.7, no clear pattern emerged between these two variables. The contour plots show overlapping distributions for both the 2AFC and multiple-choice tasks. As mentioned earlier, the contour at the 180 degrees error angle will be analyzed in Section 4.5. To avoid bias from this phenomenon, further analyses are based solely on trials that correspond to the first mode of the distribution (angles $<$ 90 degrees). For this purpose, the 'Accuracy' variable is used instead of the error angle.

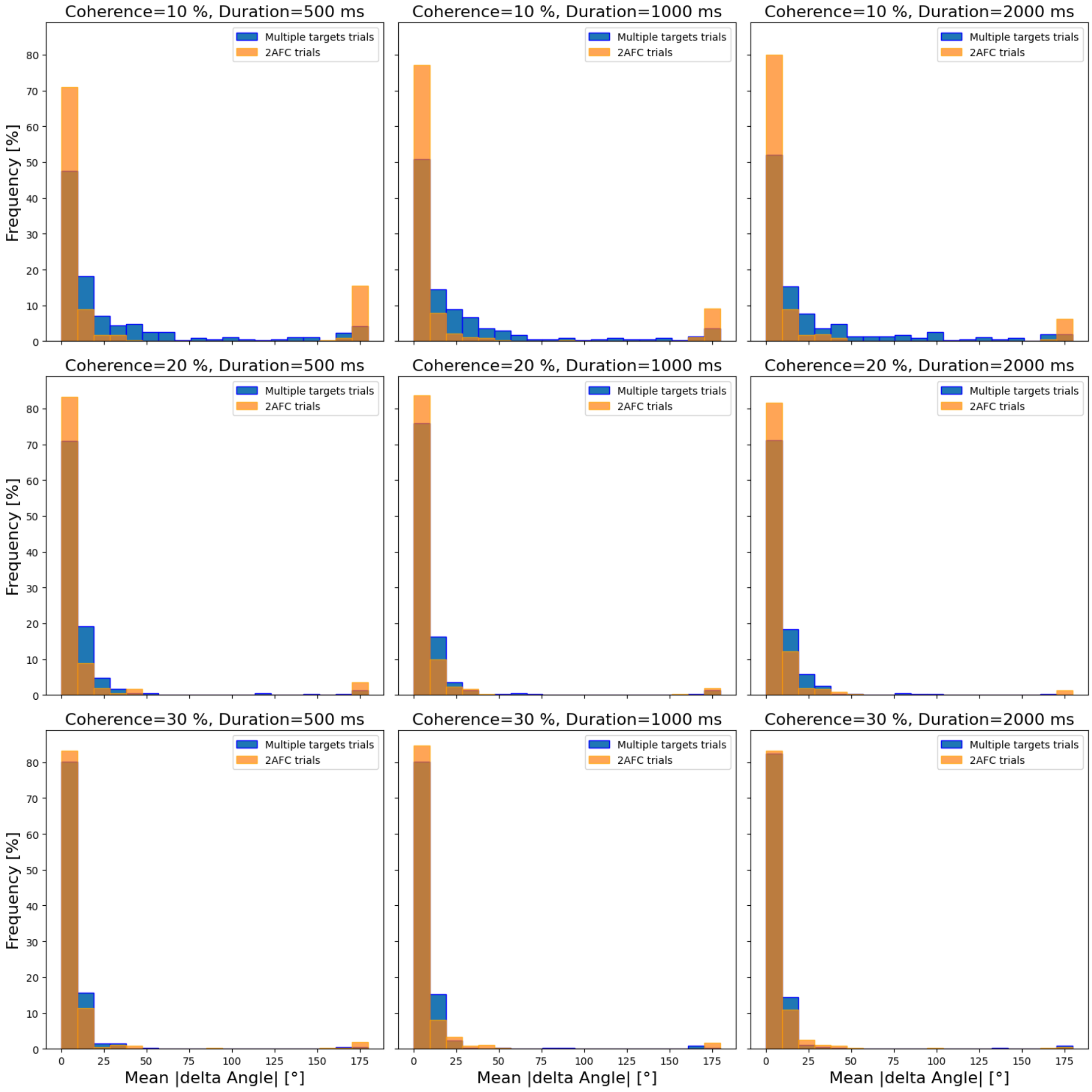

Figure 4.6: **Comparison of the distribution of error angle across the two experimental conditions:** In the 2AFC task, the distributions are noticeably narrower around 0 compared to the multiple targets task, suggesting more consistent accuracy among participants in the 2AFC task likely due to the limited choice set.

The accuracy performance for each participant in both tasks is illustrated in Figure 4.8. For the majority of participants, accuracy is higher in the 2AFC task than in the multiple-choice task, particularly at low coherence levels. This suggests that the structure of the multiple-choice task, where participants believe the stimulus's net direction could be any angle between 0 and 360 degrees, increases

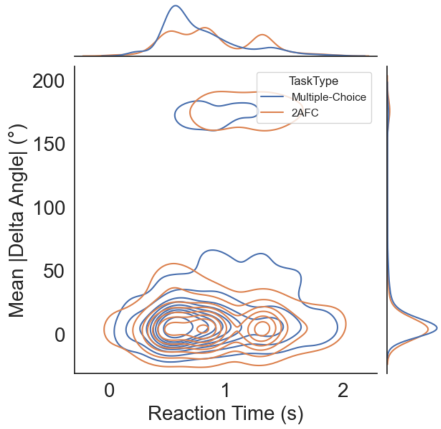

Figure 4.7: **Relationship between RT and mean delta angle error :**No clear pattern emerged between RT and mean error angle. The distributions for both task types overlap.

uncertainty and difficulty. Consequently, this leads to a greater margin of error in computing the net direction of the perceptual stimulus.

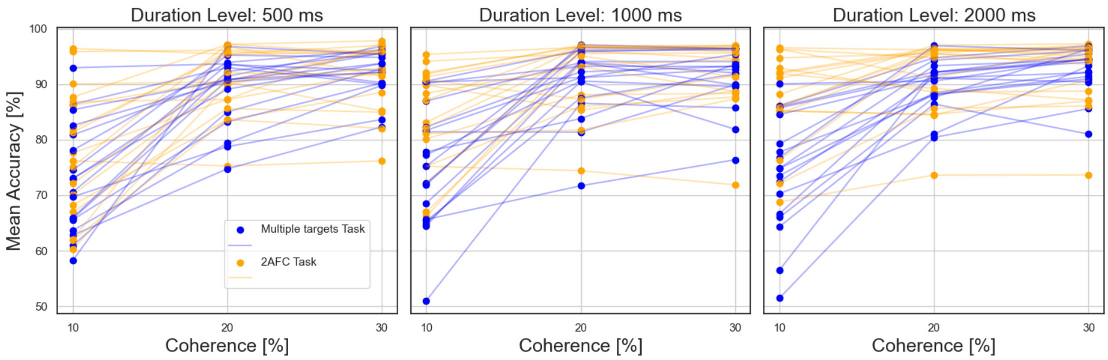

Figure 4.8: **Comparison of the mean accuracy across participants:** For lower coherence, the accuracy is larger in the 2AFC than in the multiple-choice task for the three duration levels. This tendency fades away as the coherence increases.

To quantify the observed differences in mean accuracy between the two tasks, the Wilcoxon Signed-Rank Test is performed on the untruncated datasets. Statistically significant differences are found under several conditions (Table 4.3). For a duration of 1000 ms and a coherence level of 10%, the p-value is 0.0304. At a duration of 1000 ms and a coherence level of 20%, the p-value is 0.0268. Finally, for a duration of 2000 ms and a coherence level of 10%, the p-value is less than 0.0001 (Table 4.3).

The plot in Figure 4.9 illustrates the mean accuracy across different stimulus

Duration Coherence	500 ms	1000 ms	2000 ms
10%	0.1540	* 0.0304	*** 0.0000
20%	0.3038	* 0.0268	0.0665
30%	0.3692	0.3247	0.6095

Table 4.3: P-values from Wilcoxon tests for different durations and coherence levels on the multiple-choice task.

exposure duration for multiple-choice and 2AFC tasks. When examining the 10% coherence level, emphasized by the red arrows, we observe a significant increase in the difference of accuracy between the two tasks as the stimulus duration increases. This trend is reflected in the p-values reported in Table 4.3. For the 10% coherence level, the p-value decreases from 0.1540 for 500 ms, to 0.0304 for 1000 ms, and further to 0.0000 for 2000 ms. Moreover, the plot allows us to extend this interpretation by showing that the difference increases solely because the accuracy in the 2AFC task improves, while the accuracy in the multiple-choice task remains constant across the three levels of stimulus exposure duration.

In order to statistically compare the two tasks in the truncated dataset, a mixed effects model is required as it handles missing values effectively. After truncating the datasets, the number of trials retained for each parameter combination differs between the two tasks, resulting in designs that are no longer perfectly balanced. Specifically, we will focus only on trials with a coherence of 10%.

A mixed effects model with a random intercept for each subject is performed to examine how the dependent variable, accuracy, relates to the task type and duration levels. The model includes fixed effects for the type of task (Multiple-Choice or 2AFC), the three stimulus exposure duration levels (500, 1000, or 2000 ms), and their interaction. The mixed effects model tested is specified by the following equation, and the results are summarized in Table 4.4.

$$\text{Accuracy}_i = \alpha + \beta_1 \cdot \text{TaskType}_i + \beta_2 \cdot \text{Duration}_i + \beta_3 \cdot (\text{TaskType} \times \text{Duration})_i + \eta_{j[i]} + \epsilon_i$$

The intercept, equal to 74.864, represents the average accuracy for the 2AFC task at a stimulus duration of 500 ms. This value is significant with a p-value of 0.028, indicating that the baseline accuracy for the 2AFC task is high. The variables for task type and stimulus exposure duration are not interpreted as they are not significant (Table 4.4).

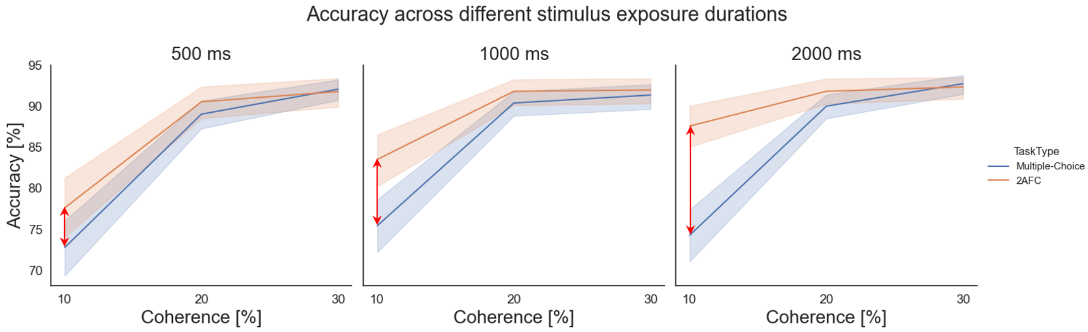

Figure 4.9: **Comparison of the accuracy across the two experimental conditions:** The 2AFC task consistently shows slightly higher accuracy than the Multiple-Choice task, particularly at lower coherence levels. The shaded areas represent the confidence intervals, indicating variability in accuracy measurements across participants. The red arrows highlight the differences in accuracy between the tasks at the lowest coherence level for each duration. These arrows emphasize that at 10% of coherence, the accuracy in the multiple-choice task does not increase with the duration of exposure whereas in the 2AFC there is substantial improvement in accuracy with the longer stimulus exposure duration.

	Coef.	**Std.Err.**	**z**	**P>|z|**
Intercept	74.864	33.967	2.204	* 0.028
TaskType[T.Multiple-Choice]	-2.228	3.037	-0.734	0.463
Duration	0.006	2.894	0.002	0.998
TaskType[T.Multiple-Choice]:Duration	-0.006	0.002	-2.676	** 0.007

Table 4.4: Summary of the mixed effects model results.

The interaction term indicates that the effect of duration level on accuracy differs between the multiple-choice and 2AFC tasks. Specifically, the negative coefficient of -0.006 suggests that as the duration level increases, the accuracy in the multiple-choice task decreases relative to the 2AFC task. For the multiple-choice task, accuracy does not increase with longer duration, whereas the 2AFC task shows a clear improvement. This trend is statistically significant, indicating a meaningful differential impact of stimulus duration on task performance even on the truncated datasets.

These results substantiate the impact of task structure on perceptual accuracy, suggesting that the sensory mechanism in the 2AFC model typically studied in laboratory is different from the sensory mechanism involved in continuous decision-making.

4.2.1 Intermediate Discussion

A famous study from Hick in 1952, stated that RT increases as a function of the number of alternatives in a choice task. His hypothesis was that the rate of gain of information is, on average, constant with respect to time. In the context of Hick's law, this leads to the prediction that RT increases logarithmically with the number of alternatives, as the information required to differentiate more alternatives grows logarithmically:

$$RT = A + Blog(n) \tag{4.1}$$

with n the numbers of possible decision alternatives, A is the intercept, and B is the slope of the function relating RT to information estimated from the data.

However, further studies revealed that the rate of gain of information can vary, challenging Hick's hypothesis. In particular, the compatibility between the stimulus and the expected response affects reaction time more than the number of alternatives. Compatibility refers to whether the expected responses based on the stimulus are intuitive and natural. Leonard (1959) demonstrated that in a highly compatible task, where vibrations were applied to participants' fingers and they had to press keys corresponding directly to the vibrated fingers, the RT function did not increase with the number of alternatives (two, four, and eight possible stimulated fingers). Thus, when stimuli and responses have a high degree of compatibility, including tasks in which participants must make saccades towards a target, the Hick law has limited applicability.

Schneider and Anderson (2011) noted that many experiments that do not conform to Hick's law involve highly compatible situations that do not require memory. Thus, memory capacity might be a key factor in the empirical limitations observed in Hick's law for decision-making tasks. [31]

Moreover, it has been demonstrated in the context of perceptual decision-making tasks that sufficient practice can render RT independent of the number of alternatives. For example, Wifall, Hazeltine, and Mordkoff (2016) confirmed this phenomenon in their experiment involving the identification of simplified Chinese characters. Participants performed the task with eight alternatives over six sessions of 640 trials each, followed by sessions involving two, four, or eight alternatives. Although Hick's law was observed in the initial sessions, by the end of the experiment, the difference in mean RT between eight and two alternatives was insignificant. [35].

In our data, as shown in Figure 4.5, there is no clear trend indicating a lower RT in the 2AFC task compared to the multiple-choice task, where the alternatives are continuous along a circle. Based on the aforementioned literature, this could be due to the task being too compatible. In our case, the degree of difficulty with coherence levels of 10%, 20%, and 30% might be too intuitive, resulting in no RT differences between the two conditions. Additionally, our task using the RDM paradigm does not involve memory use except in a minority of cases where the participants commit to the movement a long time after the stimulus has switched off.

Moreover, the learning effect represented on Figure 5.4 (available in Appendix) indicates a significant decrease in RT across the sessions for all participants. It is important to note that the 2AFC task involved five times fewer trials than the multiple-choice task. This extensive practice effect in the multiple-choice task could contribute to reducing the expected difference in RT between the two conditions.

The study by Churchland, Kiani and Shadlen trained two monkeys on a perceptual task similar to the one used in this thesis, incorporating an RDM paradigm. Two conditions were compared a 2AFC task and a 4-choice task. The RT as well as the accuracy were measured. As show in Figure 4.10, the RTs were slightly longer in the 4-choice task than in the 2AFC task such a difference is particularly pronounced at coherence levels below 10%. Our data do not show such a difference supposedly because higher coherence levels than the found threshold are used. Furthermore, it is intuitive that as the number of alternatives increases, the level of

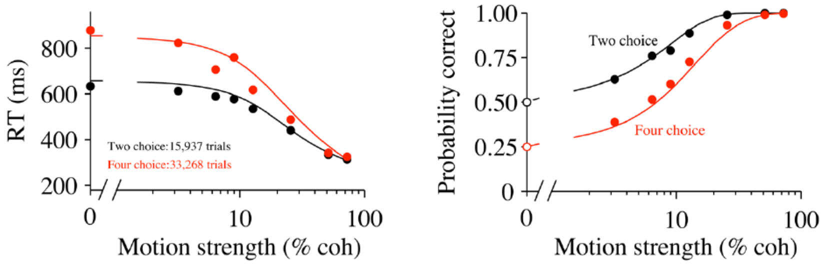

Figure 4.10: **LEFT - Mean RTs for the 2-choice and 4-choice task:** RTs are slightly longer in the 4-choice task than in the 2AFC task such a difference is particularly pronounced at coherence levels below 10Ḟrom Churchland, Kiani and Shadlen, 2008 [16]. **RIGHT - Comparison of accuracy in the 2-choice and the 4-choice tasks:** Accuracy started at chance level for 0% coherent motion and reached close to perfect performance for the highest coherence levels. At intermediate coherence levels accuracy was lower in the 4-choice than in the 2-choice condition. From Churchland, Kiani and Shadlen, 2008 [16].

uncertainty also rises, assuming all other conditions remain the same. Therefore, it is expected that the brain requires more evidence before reaching a decision. As for the accuracy depicted on the right of Figure 4.10, accuracy starts at chance level for 0% coherent motion and reaches close to perfect performance for the highest coherence levels. At intermediate coherence levels, accuracy is lower in the 4-choice than in the 2-choice condition, reflecting the lower prior probability of each choice given four alternatives.

These observations align with our data plotted in Figure 4.9, where participants' performances exhibit significant differences between the two conditions, especially at coherence levels below 20%. Several studies support these findings, with the study by van Maanen et al. (2012) providing a detailed focus on this specific topic. [6] [7] [30]

To the best of my knowledge, no scientific work published has observed that accuracy does not improved with increased stimulus duration in a continuous decision-making task. Here, we developed some hypotheses on this phenomenon inspired by a study by Yoo et al. [37] When the participant knows that the stimulus will move either to the right or to the left, they can prepare their sensory system to detect this specific direction. In tasks involving discrete decisions among fixed options, participants might adopt a strategy of focusing on a subset of cues rather than evaluating all available information. They tend to disregard points moving in non-horizontal directions effectively eliminating less informative cues from their decision-making process. Evidence towards one target or the other accumulates over time, allowing for improved performance as the stimulus exposure duration increases.

In contrast, during continuous decision-making, the goal is not necessarily to find the optimal option because none are predefined. Instead, the objective is to find a course of action that is sufficiently good. Participants seem to judge that increasing the exposure time to the stimulus does not improve their response, as they typically initiate movement before the stimulus ends. This behavior indicates a different approach to decision-making under continuous conditions [37].

4.3 The impact of target placement on performance

In this section, significant differences in performance among the ten targets are investigated, as well as a potential prior preferred direction of movement by participants. We suspect that the observations regarding the performance comparison of horizontal movements in the multiple-choice task with those in the 2AFC may be underestimated. The fact that the target in the 2AFC task are placed at 0 and 180 degrees could influence the results. We believe that the significant difference in mean error angle between the two tasks would be larger if the targets used for the 2AFC task were different from any cardinal coordinates.

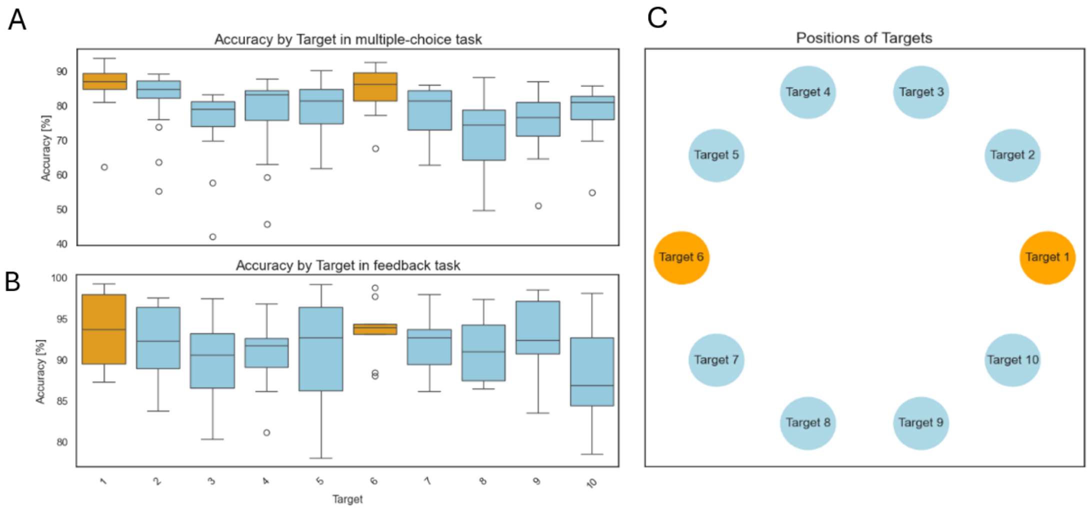

Figure 4.11: **A - Accuracy distribution across the ten targets in the multiple-choice task:** Higher mean accuracy for the orange horizontal targets, compared to others. **B - Accuracy distribution across the ten targets in the feedback task:** Overall, accuracy is higher than in the multiple-choice task, with the horizontal targets showing superior accuracy. **C - Positions of the ten targets:** Targets 1 and 6 are emphasized as they are used in the 2AFC task. Only trials corresponding to these two targets are used in the multiple-choice dataset for comparison with 2AFC task performance.

The graph displayed in Figure 4.11A illustrates the accuracy distribution across the ten targets in the multiple-choice task, with particular emphasis on two targets, colored orange, which correspond to those used in the 2AFC task. The graph reveals a higher mean accuracy for the horizontal targets compared to others, suggesting that additional factors may affect performance such as a biomechanical favour movement. Moreover, the median accuracy for target 1 is slightly higher than for target 6. The ease of movement towards the right can possibly be explained by the fact that participants use their right hand which could influence performance. This minor discrepancy is supported by data from the feedback task with 100% coherence in the stimulus (Figure 4.11B). Those two horizontal targets demonstrate a narrower interquartile range, indicating more consistent responses among participants.

A Kruskal-Wallis test confirms significant differences between at least one pair of targets, yielding a p-value of 1.43e-07. For post-hoc analysis, Dunn's test with a Bonferroni correction is utilized. This non-parametric test compares the ranks of different groups and adjusts for multiple comparisons to control the Type I error rate. Targets 1 and 6 differ significantly from all other targets except each other as shown in the heatmap in Figure 5.5 in the Appendix section. As the median accuracy of those targets is also the higher, they are significantly higher than all the eight other targets. The tendency to do better for certain targets, such as the horizontal ones, might show a natural or learned ability to judge some directions easier than others.

The bias between different targets is further investigated by comparing the frequency of movements directed towards each target relative to the total number of trials, rather than target-specific accuracy. Figures 4.12 depict the first and last twenty movements of a random participant. These figures aim to explore a potential prior mechanism in selecting a direction. In the first twenty movements, four incorrect movements are directed towards the horizontal targets, compared to none misclassified movement in the last twenty trials. It appears that the participant is more comfortable performing horizontal or vertical movements, which could be attributed to a preference for cardinal directions or the physical comfort of reaching these positions. Participants' performance might also be linked to subconscious cues or internal heuristics they use to guess directions. Any grouping seen around the ten targets is therefore a result of their cognitive and perceptive strategies rather than a response to a clear cue of target locations as participants didn't know about the ten specific targets. They are told that stimuli could move in any direction from 0 to 360 degrees, which makes them think that the directions were random and continuous, not discrete.

Further analyses are needed to extend this observation to all participants. The Figure 4.13 illustrates the distribution of movement directions in the first compared to the last session averaged by participant. The number of trials for each target in one session is equal, and as the data are aggregated across all participants, each target in one session should have 162 associated trials (3 levels of coherence x

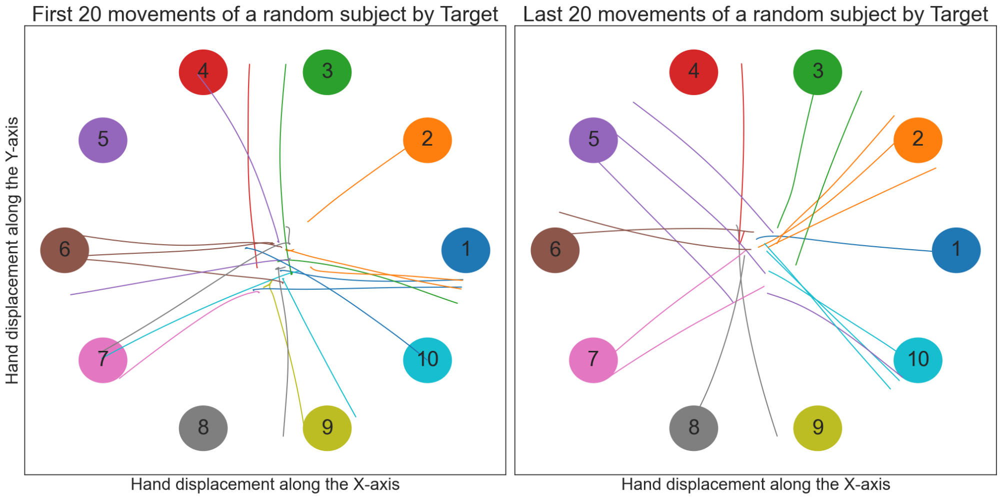

Figure 4.12: **LEFT - First twenty movements of a random subject by target:** Each color represents one of the 10 possible net motion directions of the stimulus. A line is colored based on the target towards which the stimulus was moving. A total of four incorrect movements are directed towards the horizontal targets. The two horizontal targets are chosen more frequently than others. There is a clear pattern of vertical movement, but no target was placed in that direction. **RIGHT - Last twenty movements of a random subject by target:** None misclassified movement towards the horizontal targets in the last 20 movements. This suggests an improvement in accuracy over time.

3 levels of duration x 18 participants). Ideally, the figure should be a decagon. The left plot shows that targets 1 and 6 are privileged in the first session. The tenth session shows a relatively even spread across targets, with less significant preference for horizontal directions. Initially, participants tend to perform more movements towards the horizontal targets, indicating an intuitive tendency for horizontal movements. This increases the likelihood of accuracy associated with these targets, as even when unsure about the net stimulus direction, participants generally perform horizontal movements. Therefore, comparing only these two targets with the 2AFC task could bias the results as these targets show higher performance than the other eight. However, we doubt that changing the location of the two targets chosen for the 2AFC would increase the error rate proper to this task. If targets 3 and 8 are used in the 2AFC paradigm, it would less likely increase errors in the 2AFC task, whereas comparing this rate with the data collected for targets 3 and 8 in the multiple-choice task would result in a higher difference in performance between the two tasks. This analysis highlights the influence of target positioning on performance outcomes. We can infer that horizontal positioning

may improve accuracy.

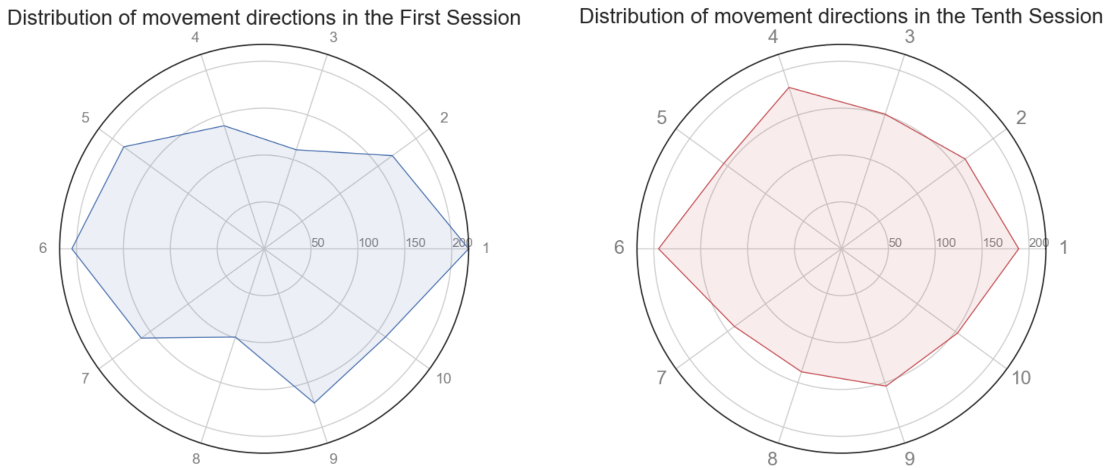

Figure 4.13: **LEFT - Distribution of movement directions in the first session:** Each trial is associated with the target closest to its direction of movement. Ideally, the figure should be a decagon if the number of trials towards each of the ten targets were equal. The horizontal targets seem to be privileged. **RIGHT - Distribution in the tenth session:** The tenth session shows a relatively even spread across targets, with no significant preference for any particular direction, except for a slight preference for the first target.

The uneven distribution in the selection of targets, with a preference for Targets 1 and 6, can be attributed to several factors. Various hypotheses are proposed and analyzed to explain this phenomenon. One possibility is that participants who initially start with the 2AFC task, which only uses horizontal directions, need some time to adapt and initially favor these two directions. They might have develop an ability to judge certain directions more easily than others. This first hypothesis is refuted based on the graph presented in Figure 4.14, which surprisingly shows that participants who perform the 2AFC task first have a lower percentage for horizontal targets in the first session compared to those starting with the multiple-choice task. It could be interesting to conduct a new experiment using the 2AFC paradigm with different target choices to see if those targets are frequently chosen by participants at the beginning of their multiple-choice sessions.

Another possibility is that we naturally have a preference for cardinal directions, or that some movements are favored because they are less energy-consuming from a biomechanical standpoint. This idea stems from a comment by a participant who mentioned that when he had no clue of the net direction of the stimulus, he would perform the same movement repeatedly. Midway through the trials, he changed his movement because he found another one that consumed less energy. These points

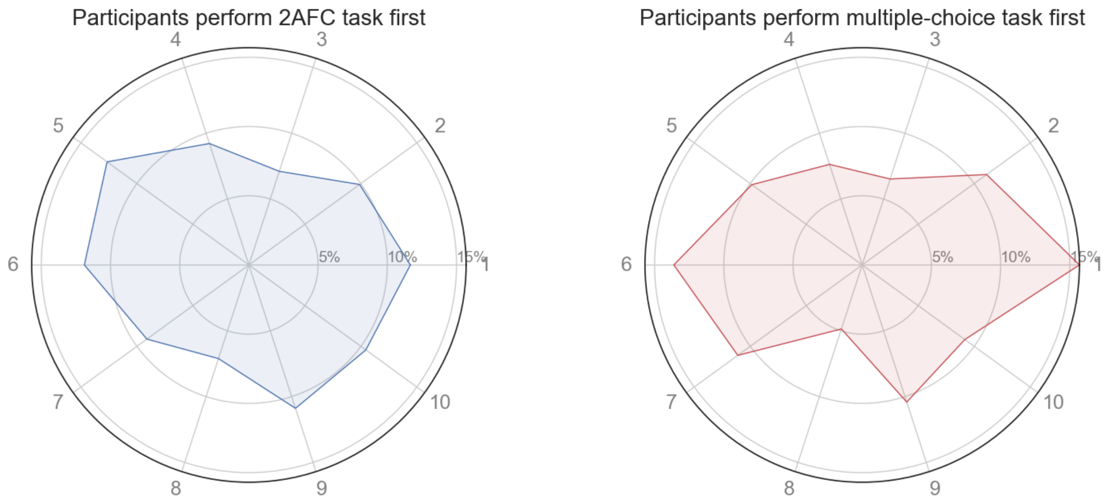

Figure 4.14: **LEFT - Distribution of movement directions for participant who perform first the 2AFC task:** Each trial of the first session is associated with the target closest to its direction of movement. Ideally, the figure should be a decagon if the number of trials towards each of the ten targets were equal. **RIGHT - Distribution of movement directions for participant who perform first the mutliple-choice task:** The horizontal targets seem to be more privileged than in the left plot.

will be further investigated in the discussion section.

4.3.1 Intermediate Discussion

Two studies directly related to this thesis, using the RDM paradigm and analyzing decision movements, suggest that biomechanical costs may bias movement selection.

A study by Pilly and Seitz hypothesizes a potential link but does not investigate it further. They state: "While it is potentially interesting to consider interactions involving the eight motion directions, there is little theoretical ground to justify such an investigation, especially considering that all the tested directions are non-cardinal" [30].

In Ayuno Nakahashi's doctoral thesis, the author justifies the positioning of two circular targets to reduce the biomechanical costs of the associated reaching movements [28].

A paper by Cos I, Bélanger N, and Cisek P. is entirely dedicated to the theme of this section. The study explores the influence of predicted biomechanical properties on motor decision-making. The authors base their work on two theoretical concepts: end-point mobility and admittance. The former focuses on the effects of joint configuration and spatial variations due to the structure and mass distribution of the arm, addressing the mechanical and geometric aspects of the system. The latter centers on the elastic properties and resulting anisotropies, focusing more on material properties and the system's elastic response to applied forces.

Both metrics can be expressed as tensors and represented as ellipses whose axes indicate directions of maximal and minimal sensitivity. In the case of end-point mobility and admittance, these axes approximately align. Trajectories aligned with the major axis of this ellipse are considered biomechanically easier than those aligned with the minor axis.

The authors design an experiment where participants have to choose between two reaching movements with different combinations of properties. In some conditions, the trajectory distance between the two targets is different. They find that biomechanical properties strongly influence movement selection. Participants prefer movements whose final trajectory is better aligned with the major axis of the mobility ellipse. If the selection criterion was purely visual, the preference for either target would be similar regardless of whether it is approached along a major or minor axis of the ellipse.

This study suggests that the brain regions involved in trajectory planning and control also actively participate in choosing between different movements. The findings indicate that the nervous system can predict the biomechanical properties of potential actions before movement onset and that these predictions can influence the decision-making process. This observation demonstrates an intimate integration between action selection mechanisms and movement planning, showing that the central nervous system possesses at least an implicit knowledge of biomechanics before movement onset. The authors do not specifically quantify the contribution of each potential biomechanical factor in influencing selection [18].

Those findings could be a first step in justifying the significantly different performances between the various targets, although the ellipse they refer to in the article does not seem to exactly match the one that emerges from our data in Figure 4.13.

4.4 Variability and improvement in participant performance across sessions

In this part of the thesis, the reasoning focuses on revealing how instructions, such as the presence of a feedback, could influence performance on similar perceptual stimulus tasks and attest to learning.

The graph on Figure 4.15-LEFT illustrates fluctuations in the accuracy of each participant over several sessions in the multiple-choice task. Each color represents a different participant, and each point reflects the average accuracy of the participant for a given session. We observe variable trends across participants. Some show significant improvements in accuracy over time, while others display fluctuations. Accuracy ranges widely, from 55% to 90%, indicating considerably variable performance among different participants. The second graph on Figure 4.15 displays the overall trends in accuracy for each participant across all sessions, with trend lines fitted as linear approximations. All participants exhibit positive slopes indicating improved accuracy across sessions, but the steepness of these slopes varies, indicating that some participants learn or adapt to the task more quickly than others.

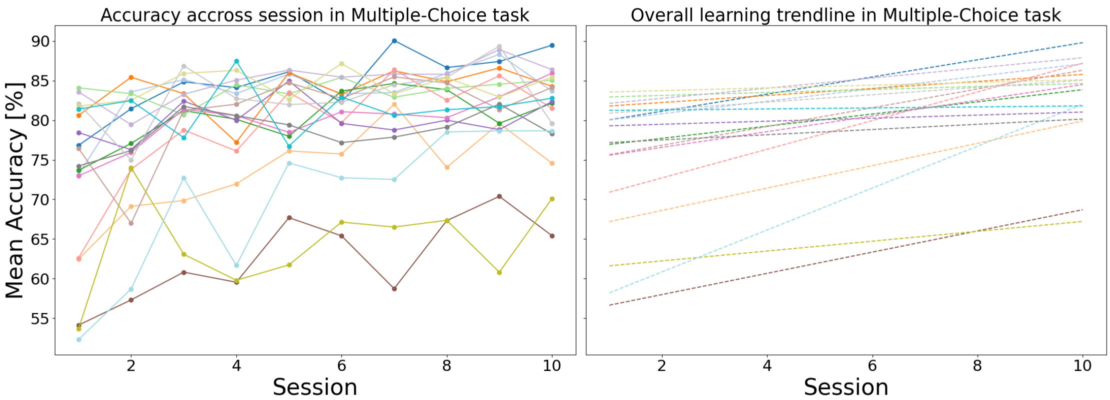

Figure 4.15: **Accuracy across time per participant in the multiple-choice task:** Accuracy ranges more broadly, from 55% to 90%, with participants showing a steady and consistent improvement over time. The trendlines predominantly show upward trajectories, indicating a general trend of learning and adaptation throughout the sessions.

A linear mixed model is employed to analyze data collected from the multiple-choice task, with the mean error angle serving as the dependent variable. The coherence level, RT, and session are incorporated as fixed effects in the model. To account for individual differences—highlighted by the findings in Figure 5.3—each subject is treated as a random effect. The mixed effects model is particularly pertinent in the context of investigating learning effects as it accommodates repeated measurements on the same participants. The model specification is as follows:

$$\text{MeanErrorAngle}_i = \alpha + \beta_1 \cdot \text{Coherence}_i + \beta_2 \cdot \text{Duration}_i + \beta_3 \cdot \text{Session}_i + \eta_{j[i]} + \epsilon_i$$

The significant coefficient for the session is -1.262, indicating a progressive improvement over time resulting in a decrease in mean error angle. The variance among participants is notably high, with a coefficient of 74.2, underscoring the necessity of employing a linear mixed model to appropriately capture the variability in our data.

The learning effect is investigated in the 2AFC task. As this task includes feedback after each trial, we suspect the performance to increase across the session particularly from the first to the second session. The Figure 4.16 depicts the accuracy of participants over time in the 2AFC task. Accuracy is generally high, mostly between 80% and 100%, with some participants showing significant drops in performance in certain sessions. Despite fluctuations, many participants maintain high accuracy, and there is a mix of learning, stable and inconsistent performance across sessions.

The right graph on the Figure 4.16 aligns with these observations, showing no dominant direction in the trendlines, indicating a heterogeneous learning experience among participants. These results could be due to several factors such as the lost of attention. Over time, participants may experience fatigue or a decline in attention, leading to fluctuations in performance. This could explain the significant drops in accuracy observed in some sessions. The mean accuracy in the first session is already particularly high, leaving little room for improvement. This ceiling effect might mask any learning gains that occur, making it appear as though there is less overall improvement.

To conclude, participants generally achieve higher accuracy levels in the 2AFC task. However, the multiple-choice task demonstrates more consistent improvement in accuracy among participants over time compared to the 2AFC task.

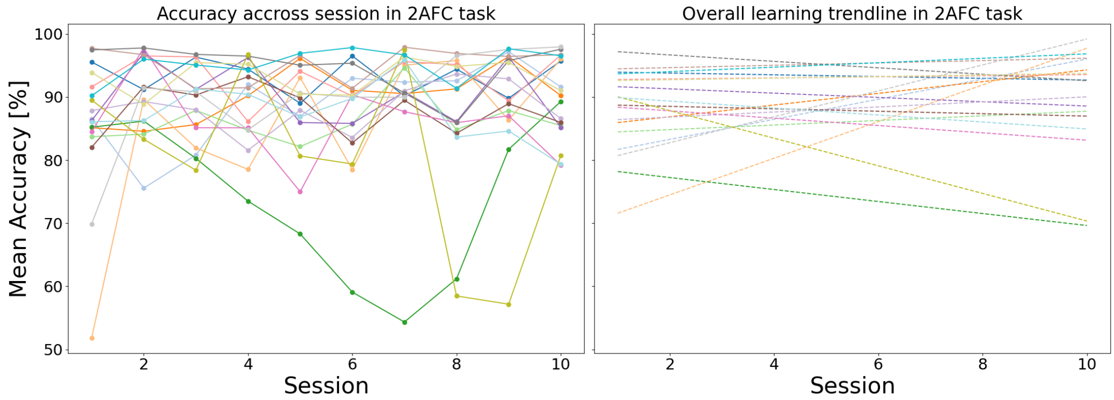

Figure 4.16: **Accuracy across time per participant in the 2AFC task:** Accuracy is generally high, with most participants performing between 80% and 100%. The trendlines reflect a mix of learning, stability, and inconsistent performance

4.5 Investigation of opposite-direction errors

In this section, the reverse motion perception phenomenon is reviewed. This illusion remains relatively unexplained and under-reported. The experiment designed during this thesis does not intend to highlight this illusion phenomenon. However, this section is added following numerous participant comments insisting that while they seem to correctly identify the axis along which the points move, they are uncertain about the direction of the motion.

Furthermore, during the analysis of the results for the main part of this thesis, the graph in Figure 4.6 reveals an unexpected phenomenon. The angle error distribution decreases as one moves away from 0 degrees but slightly increases near 170 degrees, indicating a secondary cluster centered around 180-degree errors.

The histograms in Figure 4.17 illustrate the distribution of response angle errors in the perception task. There is one large cluster centered at the true direction and one small cluster centered at 180 degrees of the true direction, indicating a significant number of trials where participants report motion in a direction opposite to the true motion. Specifically, we quantify these occurrences by calculating the proportion of opposite-direction responses as those within a window from 150 to 180 degrees (red window). Our findings show that this proportion stands at approximately 3.4%.

To distinguish between actual opposite-direction perceptions and mere guesses, we compare these responses to those approximately orthogonal to the true direction, defined as a span of 30 degrees centered around an error angle of 90 degrees, specifically a window from 75 to 105 degrees (yellow window). The proportion of orthogonal direction responses is roughly 1.8%.

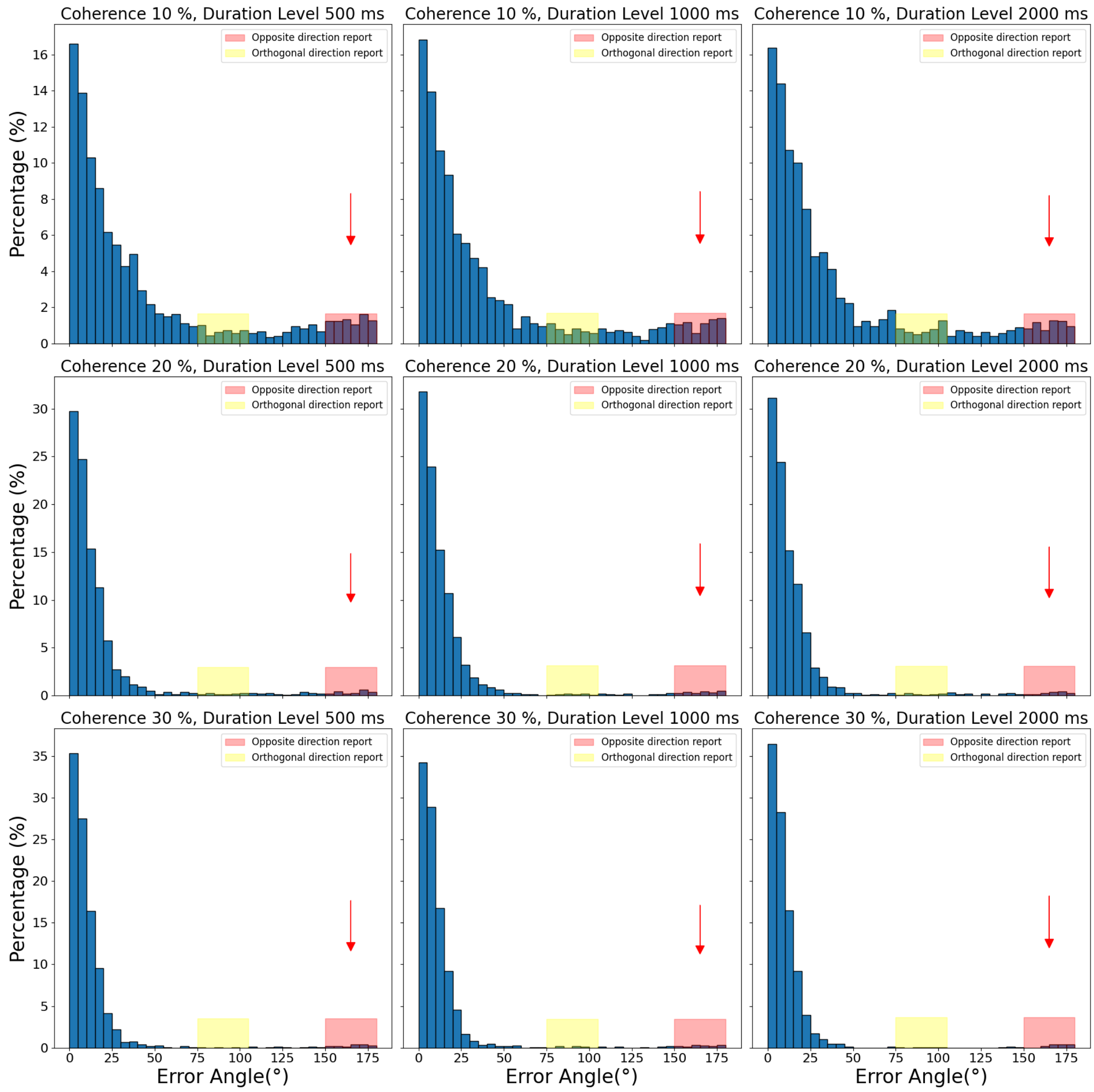

Figure 4.17: **Distribution of response angle errors by condition:** There is one large cluster centered at the true direction, and one small cluster centered at 180 degrees of the true direction, indicating a significant number of trials where participants report motion in a direction opposite to the true motion.

Given that both the opposite and orthogonal direction ranges span 30 degrees, uniform guessing should yield equal reports in these ranges. The difference between these proportions is about 1.6%, suggesting true opposite-direction perceptions as shown by Figure 4.18-LEFT. This measure, inspired by Bae and Luck, is conservative since imprecise perceptions of true motion are more likely to fall within the orthogonal range than the opposite range.

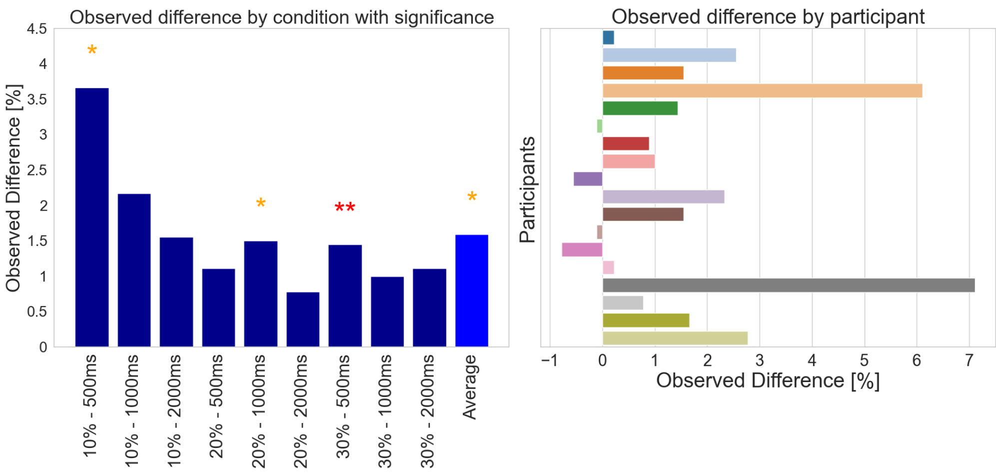

Figure 4.18: **LEFT - Observed difference by condition with significance:** This bar chart illustrates the difference between the proportions of opposite-direction and orthogonal-direction responses for various combinations of coherence levels (10%, 20%, 30%) and duration levels (500ms, 1000ms, 2000ms). Statistical significance is denoted by asterisks: one asterisk (*) for p-values less than 0.05 and two asterisks (**) for p-values less than 0.01. **RIGHT - Observed difference by participant averaged by condition:** This horizontal bar chart shows the difference between the proportions of opposite-direction and orthogonal-direction responses for each participant. The differences vary significantly across participants, highlighting substantial individual differences in motion perception.

To determine the statistical significance of these observations, we utilize permutation testing, without assuming normal data distribution as the p-value of the Shapiro-Wilk test is 0.0048. The permutation test yields a p-value of 0.0266, which suggests that the observed difference significantly deviates from what could be expected by random chance. Moreover, the effect of parameters such as the coherence level and duration has been investigated in the same way. The bar chart in Figure 4.18-LEFT displays the difference between the proportions of opposite-direction responses and orthogonal-direction responses for various combinations of coherence levels and stimulus exposure durations. Significant differences are highlighted with asterisks, where one asterisk indicates a p-value less than 0.05, and two asterisks indicate a p-value less than 0.01. For instance, the conditions "10% - 500ms", "20% - 1000ms", and "30% - 500ms" demonstrate statistically significant differences. Notably, the "10% - 500ms" condition shows the highest observed difference, exceeding 3.5%, suggesting a strong tendency for participants to perceive motion in the opposite direction under this condition with the lowest values for both parameters. The average observed differences show an overall trend towards a positive difference, indicating a higher proportion of opposite-direction perceptions across the conditions.

The second plot in Figure 4.18-RIGHT displays the observed difference by participant. The differences vary significantly across participants, with some, such as those represented by the light orange and dark gray bars, showing exceptionally high differences exceeding 6%. Conversely, a few participants exhibit slightly negative differences, indicating a marginally higher proportion of orthogonal-direction responses compared to opposite-direction responses. This variation highlights substantial individual differences in motion perception.

It's important to note that these results should be interpreted with caution due to the considerable variability between individuals and underscore the need for further research to understand the underlying perceptual mechanisms better.

4.5.1 Intermediate Discussion

In this section, we discuss the implications of the observed visual illusion in the RDM stimulus regarding our results and previous studies on visual motion discrimination. The RDM task is widely used, raising questions about whether prior studies might also have been affected by this visual illusion. In particular, our visual stimulus is similar to those used in previous studies, employing standard motion parameters. This similarity suggests that previous experiments could also have been influenced by a visual illusion.

Historically, studies on visual motion discrimination using RDM stimuli were conducted as 2AFC tasks. With only two choice alternatives located oppositely, the effects of the visual illusion would not be noticeable. In these tasks, a participant who has correctly identified the axis of motion but perceived the direction incorrectly would have a false trial, the same as another participant who failed to extract any motion information, even the correct axis. In our dataset, the visual illusion became evident only through comparisons between the diametrically opposed targets and the eight others. While human subjects in 2AFC tasks might have noticed the illusion with feedback, no study to date has provided a clear and confirmed explanation of this effect during the RDM task.

A study conducted by Larissa Albantakis also confirms an increase in error rates in opposite directions, dedicating an entire chapter to this phenomenon and being one of the first to give it significant attention. The study uses two target configurations for RDM stimuli: in the first configuration, the targets are diametrically opposed, while in the second, they are 90 degrees apart.

Their statistical analysis shows that participants are more accurate in the 90-degree condition, although the mean RTs do not differ significantly between the two conditions. Performance in the 90-degree condition is notably better than in

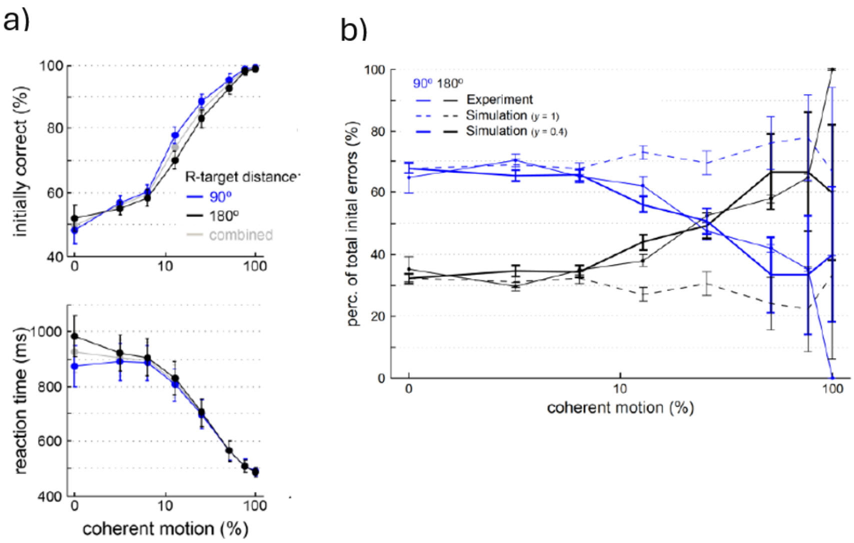

Figure 4.19: **A - Performance and mean RTs for the 2-choice 90º- and 180º-case:** Performance in the 90-degree condition is notably better than in the 180-degree condition at intermediate coherence levels: 12.8%, 25.6%, and 51.2%. Mean RTs do not differ significantly for the two conditions. From Larissa Albantakis, 2011 [8]. **B - Direction of errors relative to the correct choice in the 4-choice case:** Thin solid lines denote the experimental percentages of error trials with 90º (blue) or 180º (black) angular distance from the correct target. At low coherence levels, errors are approximately at chance level. However, at 25.6% coherence, 180º errors are more frequent than 90º errors. At higher coherence levels, the frequency of 90º and 180º errors reversed. Note that error bars increase for higher coherence as the total number of errors decreases. From Larissa Albantakis, 2011 [8].

the 180-degree condition at intermediate coherence levels as shown in Figure 4.19a) taken from the scientific paper written by Albantakis [8].

This phenomenon is highlighted by participants' comments. Some participants occasionally perceive coherent motion in the direction opposite to the correct one. This illusion likely affects responses more in the 180º condition than in the 90º condition, where the illusory direction is not a valid option. The researchers also explore a 4-choice condition, assuming that in RDM stimuli, non-coherent dots move randomly, leading to an equal distribution of errors across the three incorrect targets. At low coherence levels, errors are approximately at chance level. However, at 25.6% coherence, 180º errors are more frequent than 90º errors. At higher coherence levels, the frequency of 90º and 180º errors reverses, as shown in Figure 4.19b) [8]. According to the study, coherence levels impact the perception of the illusion, with higher coherence seeming to increase the phenomenon. Our data do not support such a conclusion.

A study conducted in 2002 by Gi-Yeul Bae and Steven J. Luck reveals that during pilot experiments, the dots often seem to move in the opposite direction to the true direction of coherent motion. They seek to determine whether this preliminary observation reflects a robust and reproducible aspect of motion perception. Although the perception of reversed motion occurs in a minority of trials, it is observed in almost all participants. They use an RDM paradigm where the direction of motion varies over 360°, and participants have to estimate the exact direction of motion, similar to the experiment conducted in this thesis. The coherence levels used are 25% and 50%, with two different exposure durations to the stimulus. [9]

In their experiment, they obtain results consistent with those of the previous study as well as ours. The distributions are bimodal, showing an increased probability of errors directly opposite to the true direction and more errors near 180° than near 90°. This second peak in opposite direction reports is evident in all combinations of coherence and duration, even in conditions with 50% coherence and a duration of 1000 ms, where few errors occur between 60° and 150°. Moreover, the opposite direction responses are as evident for the 300 ms duration as for the 1000 ms duration, ruling out direction adaptation as a cause. They find no significant difference in opposite direction reports between the 300 ms and 1000 ms durations, nor between the coherence levels of 25% and 50%, contrary to Larissa Albantakis's study. They mention that effects might be observed with more extreme parameter manipulations.

Recall that in Larissa Albantakis's study, at 25.6% coherence, 180º errors are more frequent than 90º errors but not below this level of coherence. In this study, they do not test coherence levels below 25%. Additionally, they obtain significantly higher opposite direction reports than ours, with 11% of errors at ±30° from the opposite direction and 2.8% of errors at ±30° from the orthogonal directions.

In a second experiment, they seek to understand whether these reports reflect a true conscious perception of motion in the opposite direction or an unconscious bias when participants are uncertain about the motion direction. Participants report their confidence in the motion direction for each trial. Participants state "I am quite sure" in 25% of trials with opposite direction reports and only 5% of trials with orthogonal direction reports, a statistically significant difference. This indicates that opposite direction reports often reflect a conscious perception rather than an unconscious bias. [9]

The authors propose two hypotheses to explain this phenomenon:

The first theory suggests that temporal blurring of the stimulus might cause the perception of streaks, or line segments, aligned with the direction of movement. These streaks can affect how motion is perceived because they can be interpreted as moving either in the actual direction or in the reverse direction. Research on Glass patterns has demonstrated that pairs of random dots in a dynamic display can create a global pattern of line orientations, implying that observers might perceive the motion in the reverse direction of the actual stimulus in RDKs.

An alternative explanation could be inhibition around orthogonal directions, which might artificially produce a peak in the opposite direction. If this were true, trials with higher coherence levels would show a greater number of opposite direction reports due to a stronger motion signal and the related inhibition. However, this hypothesis is rejected because there is no significant effect of coherence on the proportion of opposite direction reports in their data. [9]

The third article we review differs from the other two by stating that this phenomenon can occur even at 100% dot coherence. According to them, this phenomenon is not observable in all participants, contrary to the study by Gi-Yeul Bae and Steven J. Luck. Participants who make this type of error do so frequently, while others do not make these errors at all. Our data presented in Figure 4.18-LEFT support this second hypothesis. In their study, they also mention that some participants who initially perceive the motion in the opposite direction are able to use feedback to change their strategy and thus achieve good performance on the task [26].

Chapter 5

Conclusion and general discussion

The motivation for this research stems from the predominant use of the 2AFC paradigm in studies aimed at elucidating the neural mechanisms underlying decision-making. While this paradigm is simple and effective, it fails to capture the complexity and variability inherent in real-life decision-making scenarios. Therefore, introducing multiple choices represents a significant enhancement, enabling the validation of theories initially developed for binary choices in more realistic contexts. The goal of this thesis is to provide empirical data supporting the necessity of evolving decision-making models to include scenarios with multiple and continuous choices. Although recent research has begun to explore extending the paradigm to more than two alternatives, this remains rudimentary. To the best of my knowledge, no scientific work published has yet experimentally tested the RDM paradigm with a continuous response set encompassing all possible directions across the circle aperture of the stimulus. To address this gap, an extended experimental paradigm incorporating both traditional 2AFC tasks and a novel continuous decision-making task using RDM stimuli have been developed and conducted. The empirical data from these experiments were analyzed and led to interesting results detailed in this paper.

The elaboration and analysis of the results from these experiments demonstrated three key findings. Firstly, increasing coherence levels induce the improvement in accuracy coupled with a slight decrease in RT experimentally confirmed for both tasks. Diverging from the typical reports found in the scientific literature, the RT does not significantly differ in the continuous decision-making task compared to the 2AFC task. Moreover, this research revealed that participants tend to use distinct sensory mechanisms when engaging in 2AFC tasks compared to continuous decision-making tasks, highlighting the limitations of the traditional 2AFC paradigm. In the 2AFC paradigm, accuracy improved with increased stimulus duration, reflecting an accumulation of evidence over time, a phenomenon not observed in the continuous decision-making task.

Secondly, a detailed investigation into the impact of the ten different directions used in the multiple-choice task revealed that participants performed better when the net movement of the stimulus was along certain directions, particularly the horizontal ones. This is presumably due to biomechanically easier trajectories that are favored when participants do not have a confirmed strict response. This supports the hypothesis that the nervous system can predict the biomechanical properties of potential actions before movement onset and that these predictions can influence the decision-making process. However, there is little theoretical ground to explain the specific neural mechanisms underlying these predictive capabilities.

Thirdly, the use of a perceptual paradigm with multiple choices allowed the identification of latent phenomena in the 2AFC task. This thesis reports a bimodal distribution of the error angle, with a second peak centered around 180-degree errors. In the 2AFC task, this phenomenon is expected as there are only two possible directions: the correct one and its direct opposite, which is incorrect. However, in the multiple-choice task, it is surprising that incorrect estimations of the net direction of the stimulus predominantly fall in the direct opposite direction. One would expect angular errors to be evenly distributed across all possible responses. This visual illusion remains relatively unexplained and under-reported, likely due to the prevalent use of the 2AFC paradigm. With only two choice alternatives situated oppositely, the effects of the visual illusion are not noticeable. In our dataset, the visual illusion became evident only through comparisons between the diametrically opposed targets and the eight others.

Some limitations are specific to the design of the experiments. Firstly, it would have been beneficial to either add coherence levels below 10% or decrease the value of the three chosen coherence levels. Increasing the number of tested coherence levels would significantly extend the duration of the experiment but would provide more rigorous data. Adding levels beyond 30% would not add value to the model, as a ceiling effect of accuracy between coherence levels of 20% and 30% is already evident in our data. Although the five pilot participants confirmed that the task was sufficiently challenging, the analysis of the results showed high accuracy percentages. We aimed to avoid making the task so complex that it discouraged participants over time and biased the results. However, in retrospect, it would have been advantageous to reduce both the duration and coherence levels. Specifically, future experiments should consider setting a duration level before the prominent peak at 500 ms for the multiple-choice task. Additionally, to test the hypothesis that the non-significant RT between the two conditions might be due to an overly compatible task, further decreasing the levels of coherence could make the task more complex and potentially reveal a difference in RT.

A second limitation that could significantly improve the relevance of our paradigm is the removal of directional arrows in the 2AFC task. These arrows fundamentally alter the nature of the decision-making process, shifting the focus from sensory processing to responding to explicit cues, potentially biases the results when comparing RT between the two tasks. Removing these arrows would make the decision-making process more reliant on sensory input, hence providing a more accurate comparison.

Our findings highlight the importance of ongoing research and expanding the scope to encompass continuous decision tasks to accurately capture the complexities of real-world decision-making. Gathering detailed experimental data might eventually shed light on how neural populations encode decision information. Nonetheless, the apprehension of conducting multiple-choice tasks can be significant due to the increased complexity involved in studying and analyzing data from such tasks. Nowadays, innovative data analysis techniques and cutting-edge computational paradigms are continuously evolving. Neuroimaging techniques and advanced recording tools are increasingly capable of addressing these challenges.

A recent study by Yoo et al. (2021) emphasizes the necessity of understanding and analyzing continuous decisions. They advocate for moving beyond traditional analyses based on temporal averages and trial repetitions. Single-trial analyses will be crucial for better interpretation of data, especially when dealing with complex datasets from multiple-choice paradigms. They propose the use of dense recording techniques, such as calcium imaging and multi-electrode recording, which are particularly suited for this type of analysis. Calcium imaging allows researchers to monitor neural activity with high spatial and temporal resolution, while multi-electrode recording enables the simultaneous collection of data from many neurons, providing a comprehensive view of neural activity and interactions [37].

Furthermore, a review by Hanks and Summerfield (2016) highlights advanced techniques that are pushing the boundaries of what can be observed and manipulated in neural research, providing deeper insights into brain function and behavior. They mention the use of virtual reality environments to create controlled and immersive settings for behavioral experiments, allowing for the study of neural mechanisms underlying behavior in a more naturalistic context while maintaining experimental control. They emphasize the importance of understanding cell types, cortical layers, and projection patterns of recorded neurons to decipher the encoding of decision information. New methods targeting specific cell types for recording and perturbation open up research possibilities. Additionally, new statistical methods, including multivariate decoding models and dimensionality reduction techniques, along with advanced multi-electrode recording and MRI, are invaluable tools in this endeavor [23].

In conclusion, numerous innovative methods promise significant future discoveries in understanding human decision-making and developing more accurate and comprehensive theories about decision processes. This progress not only enhances scientific understanding but could also contributes to developing treatments for neurological and psychiatric disorders where decision-making is impaired, such as depression, schizophrenia, and autism spectrum disorders.

Declaration of Generative AI in the writing process

During the preparation of this work, the author utilized "DeepL" and "ChatGPT" to minimize grammatical and spelling errors. After employing these tools, the author thoroughly reviewed and edited the content as necessary, assuming full responsibility for the final publication.

Appendix

The following plots refer to Section 3.3:

In some trials, the reaction time (RT) is recorded as -1. This occurs when no data point exceeds the defined speed threshold after the appearance of the stimulus. Some trials exhibit an initial speed peak when returning to the start, followed immediately by the decision-making movement without a significant pause, resulting in a continuous decrease in speed, as shown in Figure 5.1.

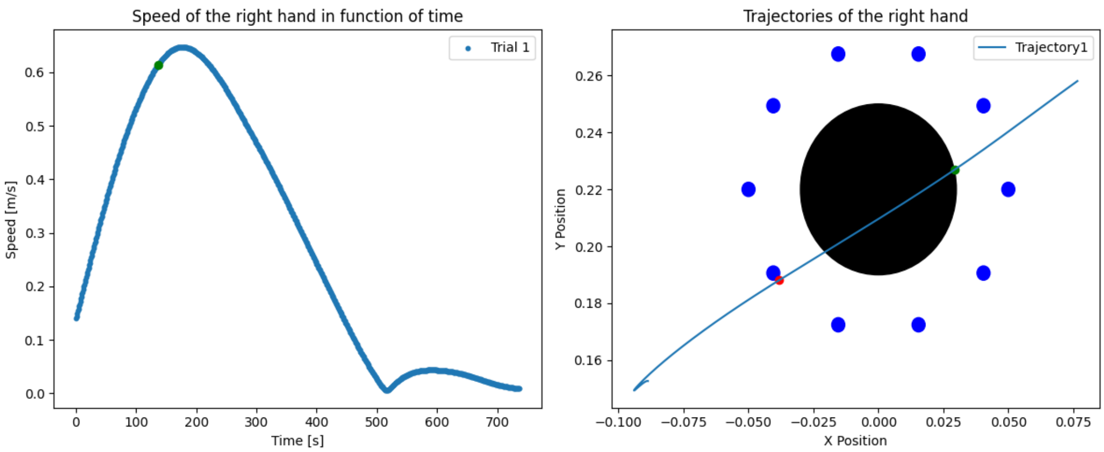

Figure 5.1: **Abnormal trial, RT is unknown:** An unique speed peak to return to the Start and continue to decrease to directly initiate the decision-making movement.

In a normal trial, there are two speed peaks: the first to return to the start, and the second to indicate the direction of the points (Figure 5.2).

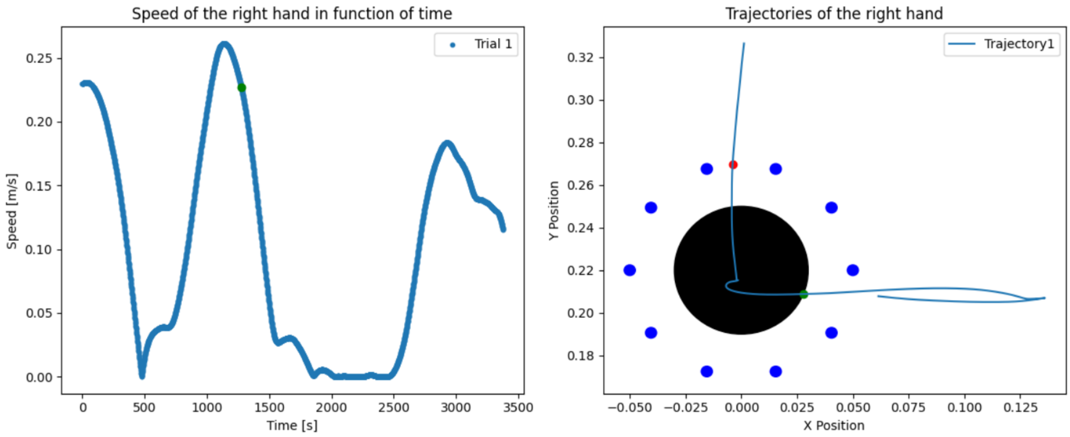

Figure 5.2: **Normal trial, possibility to calculate RT:** Two speed peaks are present, the first to return to the start, and the second to indicate the direction of the points.

The following plot refers to Section 4.1: Four participants (marked in red, gray, light blue, and grey) consistently show lower performance across various coherence and duration settings, indicating considerable individual differences. In contrast, the remaining participants exhibit relatively uniform performance, suggesting similar levels of behavioral effectiveness in the tasks.

This distinction underscores the importance of considering individual differences when assessing perceptual decision-making tasks. Moreover, there is greater variability in performance at lower coherence levels, particularly at 10%, where some participants display large error bars, indicating inconsistency in their ability to estimate the direction of the dots. Performance variability decreases at a coherence of 30%, suggesting that higher coherence stimuli are more easily and uniformly interpreted by participants, regardless of stimulus duration.

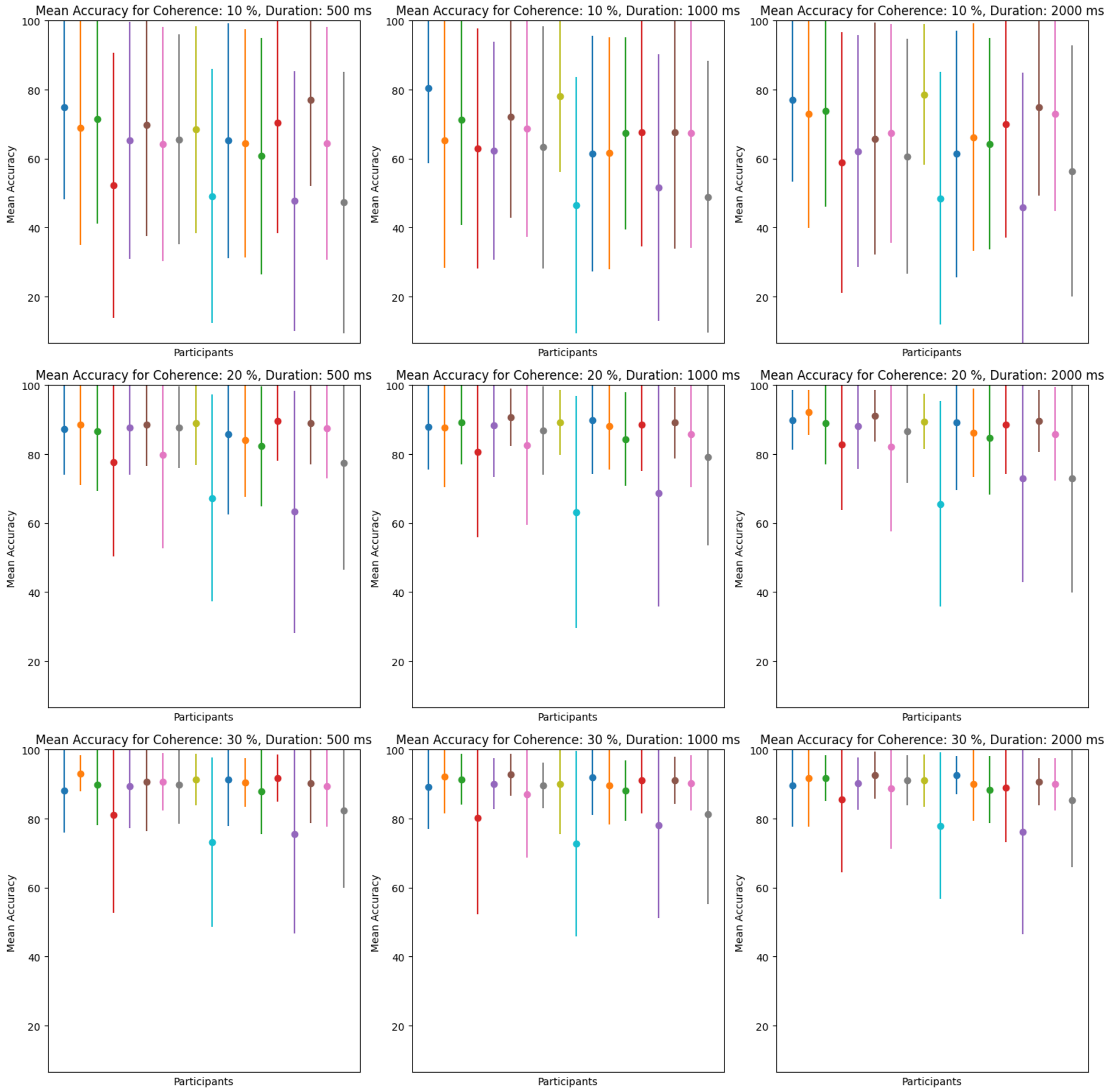

Figure 5.3: **Comparison of participant's performance:** There is significant variability in accuracy among participants. Four participants (represented by the red, gray, light blue, and grey markers) consistently exhibit lower performance levels.

The following plot refers to Section 4.2.1: Moreover, the learning effect represented on Figure 5.4 indicates a significant decrease in RT across the sessions for all participants.

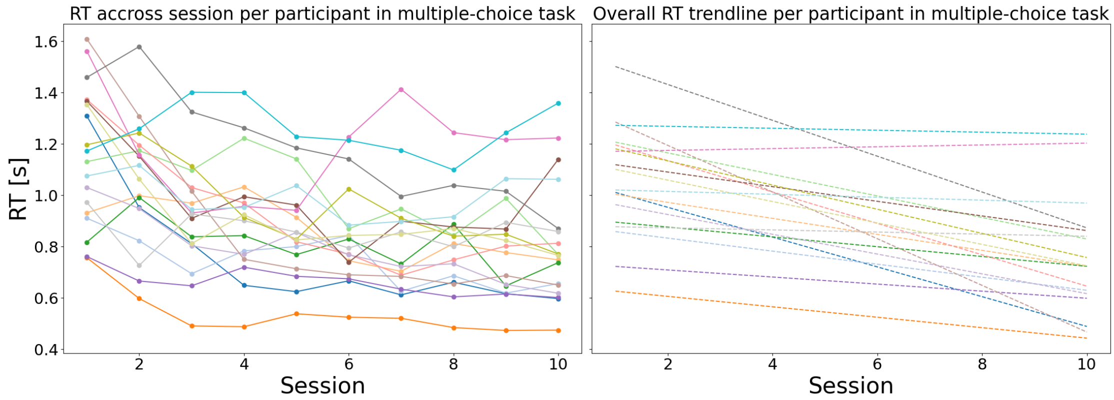

Figure 5.4: **RT across session per participant in the multiple-choice task:** The trendlines predominantly show downward trajectories, indicating a general trend of learning and quicker responses throughout the sessions.

The following plot refers to Section 4.3: For post-hoc analysis, Dunn's test with a Bonferroni correction was utilized. Targets 1 and 6 differ significantly from all other targets except each other as shown in the heatmap in Figure 5.5.

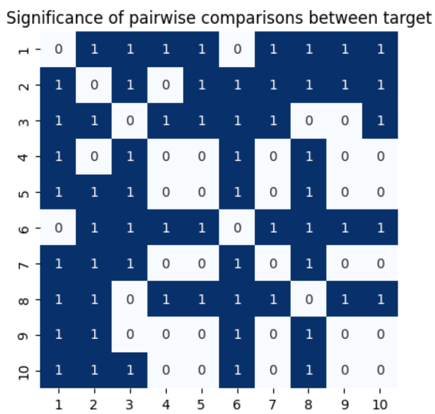

Figure 5.5: **Significative difference between pairs of targets:** Dunn's test with a Bonferroni correction was utilized for significative difference in accuracy between pairs of target. This non-parametric test compares the ranks of different groups and adjusts for multiple comparisons to control the Type I error rate. The difference is significant if the cell contains a 1. Targets 1 and 6 differ significantly from all other targets except each other.

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