COGNITIVE AND SENSORIMOTOR INTERACTIONS IN HUMAN DECISION-MAKING WITHIN A VIRTUAL ENVIRONMENT

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INTELLECTUAL PROPERTY AND PUBLICATIONS

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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ABSTRACT

There is a long tradition of studying economic decision making, where humans often fail to maximise expected gain. More recently, attention has been directed towards decision making in mathematically equivalent sensorimotor tasks, where humans often approach maximum expected gain. But numerous everyday tasks have ‘cognitive’ and ‘sensorimotor’ costs. This raises a fundamental, but hitherto neglected research question about the factors that influence decision making when an economic choice has sensorimotor risks. We created a ‘game’ in virtual reality where participants needed to hit targets in order to win points. The game required participants to choose between two targets where one was easier to hit (closer and on permanent display) and the alternative was a harder-to-hit ‘risky’ target worth more points (further away and programmed to time-out). The time allowed to hit the ‘risky’ target was the median of the individual’s baseline trials. Participants deceased their movement time during the baseline trials so the risky targets were more likely to be hit than not regardless of their distance (this resulted in the risky targets having a higher expected gain with respect to the extrinsic reward). In Experiment 1, we found participants (n = 40) were motivated by the reward (so frequently selected the higher value target). Nevertheless, the behaviour was also influenced by the sensorimotor costs, such that participants were more likely to choose the safe option (despite this decreasing expected gain) when the high reward target (worth twice as many points) was further. We found gender differences whereby women were less likely to reach for the high reward target when it was further away. Subsequently, the same selection frequencies were

found in two separate groups (both n = 40) despite the high reward target having three and five times more points than the safe option, suggesting that a sensorimotor cost threshold acts as an upper bound on the selection choice process. In Experiment 2, we added motor noise whilst keeping the expected gain constant and found that this manipulation did not affect decision making (i.e. we found same selection frequencies as in Experiment 1). In Experiment 3, we added perceptual noise and again found that this did not affect the decision making. Experiments 2 and 3 suggest that adults are well tuned to the costs of their sensorimotor actions. The data from all 200 participants showed a bias to: (i) select a risky target after a safe trial; (ii) select a risky target after a high reward target was hit (compared to when it was missed). These behavioural phenomena are well captured by a partially observable Markov decision process (pom-dp), and a pom-dp model was able to capture the behaviour by integrating extrinsic rewards and sensorimotor costs in a choice selection process. The pom-dp predicted that participants should increasingly select the risky target across multiple sessions, with the result that males and females should converge on similar selection rates across the different target distances. Experiment 4 tested this prediction with participants repeating the task across multiple sessions over three days. This resulted in an increased probability of the high reward target being selected, and by the end of the sessions the gender differences were not observed. The first four experiments always contained a known 'safe' target so Experiment 5 introduced a selection task where the choices needed to be made in a more dynamic fashion and there was not always an obvious 'safe' target. Experiment 5 confirmed that participants rapidly combine extrinsic rewards and sensorimotor costs in order to choose between targets on a trial-by-trial basis. Experiment 6 investigated decision making in younger children and showed that the combination of extrinsic rewards and sensorimotor costs occurs in even 7-8 year old children (though there was greater evidence of sub-optimal selections occurring on some trials when the age of the group was younger).

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Humans make countless decisions on a daily basis - from selecting which movement to execute through to selecting how the movement should be executed. This can be seen in even a simple activity such as picking an apple from a tree. There may be a bias towards selecting the closest apple to reach-and-pick. But what if the further apple is riper? The decision could be based on the reward only (apple ripeness) or the sensorimotor cost (the distance of the apple) or perhaps a combination of both factors (i.e. reward and cost). Little is known about the underlying mechanisms that govern such decision-making and how these factors (sensorimotor cost and cognitive reward) interact.

Decision-making is defined by the Cambridge dictionary as: “a choice that you make about something after thinking about several possibilities”. It is defined according to the MIT Encyclopaedia of Cognitive Science as: “the process of choosing a preferred option or course of action from among a set of alternatives” (Wilson & Keil, 2001). When the probability is known the decision-making is being made under risk, however when the probability is unknown, the decision-making is being made under uncertainty. Uncertainty plays a big role in most of the decisions we face in daily life. The possible options can be explained by a probability distribution on potential outcomes that takes the form:

$$(P_1, O_1; \dots\dots; P_n, O_n) \tag{1}$$

where O_1, …, O_n represents potential outcomes, and P_1, …, P_n, represents the corresponding probabilities. The decision problems depend on the level of knowledge about the probability. Therefore, they are divided into three categories; complete uncertainty (no knowledge about probability), ambiguity (some knowledge about probability), and risk (complete informed probability) (Martinez-Correa, 2012).

This thesis is concerned with two different types of decisions that humans make on a daily basis: 'cognitive' and 'sensorimotor' decisions. The vast majority of the research literature on human decision-making has focussed on cognitive decision processes (e.g. economic decision-making). More recently, there has been interest in how humans choose between two different actions. There have also been attempts to conceptualise sensorimotor control as a continuous set of decisions. This thesis will distinguish between the continual processes of control that are involved in sensorimotor action (which will be called 'sensorimotor control') and the discrete choices that need to be made about which action is chosen (that will be called 'sensorimotor decision-making'). Nevertheless, it is recognised that sensorimotor control' and 'sensorimotor decision-making' are highly integrated processes. It is further recognised that sensorimotor decision-making and cognitive decision-making are highly integrated – and the major topic of this thesis is how these different decision processes interact when humans choose one option rather than another. This introductory chapter will provide a brief summary of decision-making before providing a general overview of the sensorimotor control literature.

The consideration of the sensorimotor control literature will lead to recent work that proposes how the human nervous system makes sensorimotor decisions.

1.2 Cognitive decision-making

Expected utility theory was first developed by Bernoulli (1738). The main idea of the theory is that the best decision is the one that comes from the largest expected value. It predicts that people should choose the largest expected gain or smallest expected loss. When the expected gain or loss remains the same, people should choose each option about equally often on average, provided they have an unlimited source of funds and behave rationally.

The problem with expected utility theory is that human performance in decision-making under risk is characterised by sub-optimality. Human performance is affected by different cognitive biases that can cause some limitations and deficits when making rational decisions. Framing the outcome of human performance in terms of losses and gains with an overestimation of loss-aversion was one of the patterns noticed with sub-optimality according to Kahneman and Tversky (1979). Loss aversion can be seen as people dislike a loss (even little losses) more than they like a gain of the same size. Another feature of sub-optimality is the propensity to overweight the low probability outcomes (Tversky & Kahneman, 1992). It has also been found that humans tend to incorrectly estimate the frequency of rare events (Lichtenstein et al., 1978). The prospect theory developed by Kahneman and Tversky (1979) captures these behaviours by including a probability weighting function along with assuming that participants maximise the loss and gain trade-off.

Kahneman and Tversky (1979) proposed four components of prospect theory: (i) reference dependence; (ii) loss aversion; (iii) diminishing sensitivity; (iv) probability weighting. According to the theory, people obtain utility from gains and losses, which are evaluated against a reference point instead of an absolute value. This assumption is called a “reference dependence”, which can be reflected in our perceptual system. For example, our body is more adjustable to changes in the temperature (increase or decrease) rather than the absolute degree of change. The second component of the theory is loss aversion, which can be defined as people disliking a loss (even small losses) than like a gain of the same size. The theory value function considers winning £100 less valuable compared to losing £100. The third component of prospect theory is diminishing sensitivity, which is defined by the value function concavity in the gains area and convexity in the losses area. This sensitivity means that replacing £100 gain (or loss) with £200 gain (or loss) has greater impact compared to replacing £1,000 gain (or loss) with £1,100 gain (or loss). The concavity over the gains area represents the risk-averse behaviour in people over moderate probability gain. Kahneman and Tversky (1979) found that people preferred a definite gain of £500 over a gain of £1000 with 0.5 probability. On the other hand, the convexity over the losses area represents risk-seeking behaviour. Kahneman and Tversky (1979) found that people preferred a 0.5 probability of losing £1000 over the definite loss of £500 (panel A in Figure 1.1). The last component of prospect theory is probability weighting. According to prospect theory, people weight their outcomes according to the weighted probability instead of the true probability. Thus, humans overweigh small probabilities and under weigh high probabilities. Kahneman and Tversky (1979) found that people preferred a 0.001 probability of gaining £1000 to a definite gain of £1, but they also preferred a definite loss of £1 to a 0.001 probability of losing £1000 (panel B in Figure 1.1).

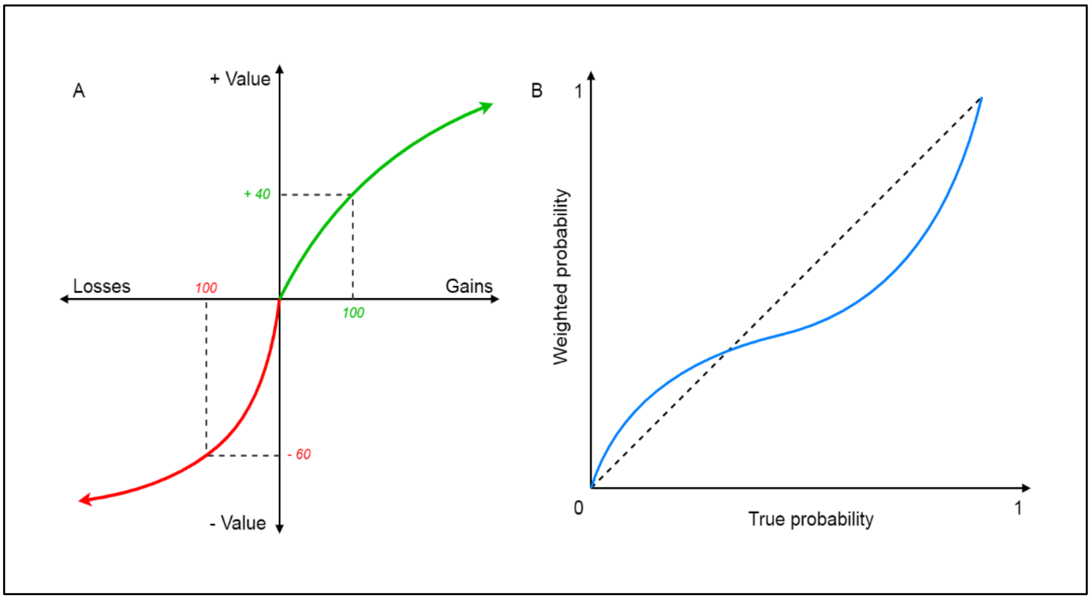

Figure 1.1 Panel A shows the prospect theory value function, the x-axis represents the gain and losses while the y-axis represents the positive or negative value. The concavity of the function over the gains represented with green arrow and the convexity over the losses represented with red arrow. Dashed lines showing the negative and positive value (-60 and +40) of the same gain or loss of £100. Panel B shows the probability weighting function, the true probability on the x-axis and the weighted probability on the y-axis. The dashed line is the linear probability function according to the utility theory, and the blue non-linear probability is the weighting probability according to the prospect theory.

The study of human decision-making developed over time from focusing on economic models into creating biological models of the proposed processes (Bossaerts & Murawski, 2015). Early economic theories, such as rational choice theory and revealed preferences theory (Coleman & Fararo, 1992; Richter, 1966), focused on choices and how these choices can be linked to maximising mathematical function (value or utility function). Subject preference was not considered of great importance within these theories, and they considered preference and choice as an equivalent. The work of Kahneman and Tversky (1979) meant that new value functions were developed to improve the fit of the original models with empirical data. Utility maximisation was the framework that started to capture the human choice behaviour in a manner consistent with the earlier economic theories.

The neuroeconomics field emerged from advances in biological research aimed at improving our understanding of brain functions and activities (Bossaerts & Murawski, 2015). Neuroeconomics focuses on the description of choice algorithms and their biophysical implementation. This way of study helped to improve understanding of how value functions are represented in the brain at a neural level. Neuroeconomic data were used mainly to improve our understanding of valuation models when data were not enough. Neurobiology studies have shown that choice under uncertainty might be based on mean variance rather than traditional expected utility theory. Decision neuroscience is a new field of decision-making where biology plays a major role in capturing the biological variations that even the best economic models fail to capture (Shiv et al., 2005). One area of research in neuroscience is studying the effect of neurotransmitters on behaviour. It has been found that an increase of dopamine level in the brain affects the economic choice of subjects and was found to be speeding the learning rate in two-armed bandit task (Pessiglione et al., 2006). However, there is some controversy over whether the information gathered from the neuroeconomics studies is relevant, and it has been argued that neuroeconomics is not important for the future of choice theory (Bossaerts & Murawski, 2015).

The efficient coding hypothesis states that economic choices are irrational because they are easily affected by variation in the local context (Summerfield & Tsetsos, 2015). Perceptual decision-making experiments usually tend to show optimal behaviour because the tasks made in single and static context. If the environment becomes more variable and violates this static condition, the decision-making behaviour will show economic-like decision-making. Other studies have found that subjects give more credits to the outcomes that are close to category boundary compared to those far away. When information about the target is variable and consistent humans integrate information robustly neglecting the redundant information. The information available affects the evaluation of feature values according to the efficient coding hypothesis (Barlow, 2013). In line with this hypothesis, subjects process information that has higher probability with higher gains. Sufficient information encoding is important to obtain good decision-making. Economical biases might be explained by a model in which the gain of neural processing is easily adaptable to the environmental context. The perceptual decision-making exhibit sub-optimal behaviour. However, the optimal behaviour may occur when the environment is stable (Summerfield & Tsetsos, 2015).

Optimal decision theories link neurobiology and behaviour in two ways; by enabling the identification of decision-making models agreement, and by improving the understanding of current data (Bogacz, 2007). Perceptual decision-making has three processes; first the sensory evidence to support the choices, then integrating the information available over time, and the last process is when a specific criteria has been checked (Mazurek et al., 2003). To decide between two alternatives, there are two models proposed; a race model and a diffusion model (Ratcliff, 1978; Vickers, 1970). According to the race model, the decision is made when the integrated evidence exceeds a specific threshold. In contrast, the diffusion model suggests that a decision is made when the difference between the winning choice and the losing choice exceeds a threshold. There are different cortical models (e.g. Shadlen & Newsome, 2001; Usher & McClelland, 2001) presented to explain the cortical process in decision-making. When deciding between two alternatives, there are two neural integrators linked to the possible alternatives, and when the activity level in one of the integrators exceeds a threshold, a decision is made. The cortical models are equivalent to the diffusion model for value that optimises their performance.

True optimisation requires a meta-optimisation that takes into consideration the benefits and costs of the internal processes employed in making decisions (Boureau et al., 2015). Boureau et al., (2015) proposed that the brain has at least two decision controllers; one is responsible for selecting the controller to perform the optimisation processes and the other is responsible for selecting the final outcome according to the controller’s preference. Choosing between alternatives involves comparing between different expected values. Finding the difference between the value of the final outcome and the cost associated with that outcome yields the net value of any decision process. Choosing the most rewarding choice depends on accurately knowing the value of other alternatives. Computational models of how the use of resource could be translated into gain: (i) assume that the particular amount of resource use gets better information (Keramati et al., 2011; Payne et al., 1988); (ii) specify some mechanisms that might produce more accurate responses (Bogacz et al., 2006; Dehaene et al., 1998); (iii) explain how complex cognitive representations might lead to a better outcome (Baum & Smith, 1997; Daw et al., 2005).

The study of metacognition aims to understand the basis of certainty states and their role in regulating mental resources to a specific task (Ackerman & Thompson, 2017). Two levels must be considered in order to understand the metacognitive processes such as; object-level processes, where basic cognitive work is carried out, and meta-level processes, where it monitors the basic-level processes to examine functioning (Nelson, 1990). In the meta-reasoning framework, the object-level processes involved in reasoning are; identifying the components and goals, generating initial responses, and selecting choices. The processes that control cognition are low level, and cue based, even in activities such as reasoning.

Current theories of decision-making are based on optimisation and might not be feasible in some situations (Bossaerts & Murawski, 2017). Bossaerts and Murawski (2017) proposed 'computational complexity theory' to deal with the computational problems that other theories cannot deal with. Rational choice theory, for instance, presents the problem of decision-making as an optimisation problem. These theories do not explain how the decision maker would behave optimally, and whether finding the optimal solution is possible. Another challenge is the utility idea in decision-making studies, where subjects are presented with limited number of alternatives (usually two). Models of human decision-making need to take into consideration the resources available to the decision maker in different decision circumstances. However, the availability of the resources is usually context-dependent. In 'computational complexity theory' the decision-making and cognitive control are linked and cannot be thought of as a separate systems (Bossaerts & Murawski, 2017).

In summary, there is a large literature on cognitive decision-making. The research literature has established that cognitive decision-making is subject to a number of biases and is often not rational. The underlying mechanisms of decision-making in cognitive tasks have been investigated extensively and a better understanding of how humans make decisions (and the neural substrates of these decision-making processes) has been developed. There has been much less work on understanding how cognitive decision-making interacts with the sensorimotor system.

1.3 Sensorimotor control

Motor control is defined as the ability to regulate or direct the mechanisms essential to movement (Shumway-Cook & Woollacott, 2007). Movement emerges from three main factors; the task, the environment, and the individual. Constraints within individual factors are cognition, action, and perception which are important to understand the full picture of motor control. There are many theories for motor control; the reflex theory, hierarchical theory, motor programming theory, systems theory, dynamic action theory and ecological theory.

Sherrington (1947) developed the reflex theory which suggested that complex behaviour could be explained through the combined action of individual reflexes that were chained together. There were many limitations to this theory – such as the fact that the reflex cannot be the basic unit of behaviour especially if spontaneous and voluntary movements are recognised as acceptable classes of behaviour because the reflex must be activated by an outside agent (Rosenbaum, 2009). Reflex theory also failed to adequately explain the movements that occur in the absence of a sensory stimulus, fast movements or the fact that a single stimulus can result in a varying response depending on context and descending commands. Finally, reflex theory was unable to explain the ability to perform novel movements.

The issues faced with reflex theory resulted in the development of motor programming theory – which was based on the central motor pattern concept (Schmidt, 1980). This concept is more flexible than the reflex theory, because movements could be activated by either sensory stimuli or the central processes. The motor programme could be identified as a central pattern generator that is the spinal motor programmes that can produce movement without any input (cortical or sensory). On the other hand, the motor control term also could be used to describe the higher level motor programme. This represents actions in more abstract way. Motor programming theory clearly suggested that the hierarchal organisation of the motor programme could store the rules of generating the movement. One of the limitations to this theory is that it’s not intended to replace the importance of sensory input in controlling movement. The central motor programme cannot be the sole determinant of action (Bernstein, 1967). Moreover, this theory doesn’t take in consideration the environmental and musculoskeletal variables in executing the movement control.

Instead, Gibson (1966) suggested the ecological theory of movement control. Gibson’s research considered how we detect information in our environment that is relevant to our action, and how this information is used to control our movement. Actions require perceptual information that is specific to a desired goal-directed action performed within a specific environment. Gibson’s theory of ecological perception focused on the role of perception in detecting information in the environment that can support the actions necessary to achieve the goal. The organisation and function of the nervous system were given much less emphasis in this theory and many researchers who follow Gibson also identify closely with the ideas of system theory (Bernstein, 1967).

System theory was developed by Bernstein (1967) and concerned mostly with the degree of freedom issue. The human body has many degrees of freedom to control, in other words, we have many joints and each joint can move in a number of different ways. Bernstein suggested hierarchical control exists to simplify the control of the degrees of freedom. The higher levels of the nervous system activate lower levels, and the lower levels activate synergies that act together as a unit. This theory has been criticised for its broad and general explanation of motor control and the fact that it doesn't account for the interaction between the organism and the environment. Thus, the ideas of Bernstein were developed further into dynamic action theories of action control.

Dynamic action theory suggests that new movements emerge due to a critical change in one of the system's control parameters (Kamm et al., 1990; Thelen et al., 1987). These control parameters are variables that regulate changes in the behaviour of the entire system. The dynamic action perspective has de-emphasised commands from the CNS in controlling the movement and emphasised the physical constraints of the movement. The motor behaviour is thought to be determined by the relationship between the physical systems of the human, and the environment in which the human operates. Combining both the dynamic and system theories of motor control produced a dynamic system model. This model proposes that the movement underlying action results from the interaction of both physical and neural components.

More recently, Shumway-Cook and Woollacott (2007) developed the ‘integrated system-based theory’ which reflects the key elements of the motor control theories discussed earlier (i.e. hierarchical, systems, dynamic action and ecological theories). This theory conceptualises movement as a product of an interaction across the task, the environment, and the individual. The task attributes mainly define and constrain the execution of a movement task. Tasks are classified based on the movement variability, the base of support (whether it is stationary or changing), and finally the manipulation requirements. The environmental constraints can be divided into regulatory and non-regulatory conditions. Regulatory conditions are factors that shape the movement while the non-regulatory conditions are those factors that may affect performance but do not directly shape the movement. The individual constraints according to this theory can be divided into three categories: action (involving the motor system), perception (factors that limit the internal integration of sensory information), and cognition (relate to attention, emotions, and motivations).

1.4 Computational approaches to sensorimotor control

Functions and activity of daily living involve a series of actions that are executed to complete a specific goal. Decision-making processes are evident in all the different levels of such an activity, such as; planning, selection, execution, feedback and correction. The initial work of the quantitative models on goal-directed movement focused on movement planning. One of the main problems is movement redundancy, which simply means that each action (such as reaching to a cup of water) has multiple possible movement trajectories.

One solution that it has been proposed the human brain uses to resolve this issue is to choose an action associated with the lowest motor cost. Most planning models concentrate on the framework of optimising cost. The system is trying to optimise performance and certain functions. There were different suggestions in the literature about what is being optimised. Some have suggested the system seeks to minimise energy (Chow & Jacobson, 1971; Rancourt & Hogan, 2001), minimise jerk (Flash & Hogan, 1985), minimise torque (Uno et al., 1989), or minimise spatial error (Harris & Wolpert, 1998) as a way of optimising the function.

Flash and Hogan (1985) suggested that the brain tries to minimise the cost of movement by minimising jerk (movement acceleration). They presented studies of the coordination of voluntary arm movements and developed a mathematical model to predict the feature of a multimodal arm movement (minimum-jerk model). Using dynamic optimisation theory, the best movement performance was determined. The best movement was defined by the minimum rate of change of acceleration (jerk). They compared their model to human subjects performing a voluntary movement and found similarities between the predicted and measured trajectories. The steepness of the rising and falling velocity, acceleration curves, and time to acceleration were similar between the predicted and measured results.

There are different frameworks and mechanisms proposed in the literature that might be used by the brain to optimise movement (Franklin & Wolpert, 2011). First, predictive control can be used to overcome common problems like delays and noise. Second, impedance control can be used to control the noise and uncertainty in the system. By increasing the resistance to displacement, the impedance control mechanism controls the changes in the sensorimotor system. Third, learning mechanisms can be used by the brain to optimise movement control. Humans are learning machines and they develop, learn, and adapt with time. Learning can be used to overcome some of the problems mentioned earlier, like nonlinearity and non-stationarity. Two mechanisms specifically proposed in the literature for movement control are Optimal Feedback Control and Bayesian Decision Theory and they are discussed in detail below.

Optimal feedback control (OFC) is a model proposed by Todorov and Jordan (2002) and suggests that the system is trying to optimise the feedback gained from a movement. OFC is concerned with studying the optimisation of cost function and modelling human performance. The controller in this framework needs an optimal estimation of the system and appropriate adjustment of the feedback gained. An optimisation technique is used to find the feedback control law that minimises the error in task performance. The optimal feedback control law is initiated after the task is selected, then a motor command is sent to the muscle to execute a specific function. Another signal ('efferent copy') is simultaneously sent to the optimal state estimator to overcome the delay in the feedback and correct the movement pattern as the function is executed (i.e. reducing error). The task-relevant errors are corrected and those errors irrelevant to the task are ignored (the so called minimum intervention principle). This principle is used in the OFC model to minimise the potential effect of noise. The feedback gains are optimised in this framework and therefore the movement. To optimise the movement, the Bayesian decision theory framework is used (Figure 1.2).

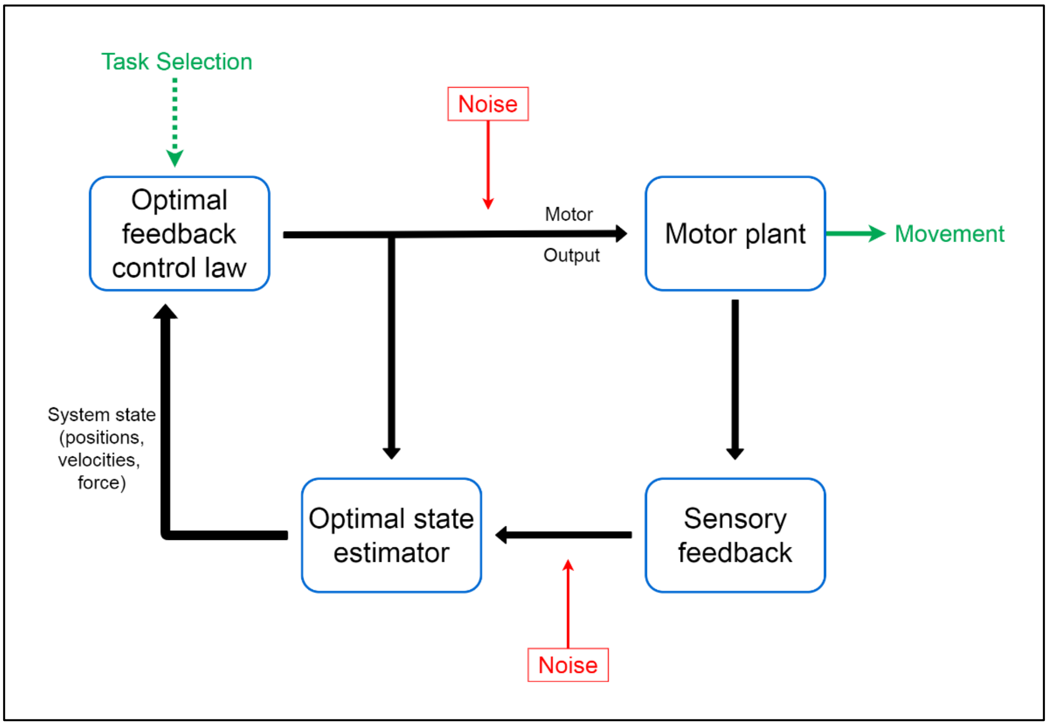

Figure 1.2 Optimal feedback control (OFC) framework as proposed by Todorov & Jordan, (2002).

Bayesian decision theory (BDT) is a framework that consists of Bayesian inference and decision theory (Blackwell & Girshick, 1954). The framework is used to describe how the nervous system could perform optimal estimation and control the inherent uncertainties within the system. This theory relies on prediction of both the internal and external state of the world. Knowing the state of the world and the objectives of the movement (the decision) are the main two challenges in Bayesian decision theory. When Bayesian estimation provides an accurate estimate of state, then decision theory can be used to choose the optimal function given the inherent uncertainties within the system. According to Bayes' rule, the probability of receiving new information (termed the likelihood) is combined with the prior beliefs to obtain the probability of different possible states (termed the posterior). The other part of the BDT framework is concerned with the 'decision' and deals with the problem of selecting the decision or action based on the current information. The goal is to minimise the expected loss given our current knowledge. This loss function quantifies the value of taking each possible action for each possible state of the world, L (action, state). To calculate the optimal action, the expected loss for a specific action is calculated and this loss is averaged across the possible states weighted by the degree of belief in the state:

$$\sum \mathbf{L}(\mathbf{action}, \mathbf{state})\mathbf{P}(\mathbf{state}|\mathbf{sensory\ input}) \qquad (2)$$

Where ∑ denotes a summation over all possible states, and then the action which has the smallest expected loss can be chosen as an optimal action.

In summary, good progress has been made in developing computational models of sensorimotor control. These models provide some insights into possible mechanisms that the brain could use to deal with the complexities of controlling movement in an uncertain world. The work in this thesis is based on an experimental task where participants must choose between targets that have different sensorimotor costs. The sensorimotor costs were manipulated by pacing targets at different distance. The further targets had a higher sensorimotor cost because reaching to further targets places greater demands on the postural control system. The development of postural stability is an important milestone in childhood development, and the ability to maintain a stable posture is a foundation for a myriad of different motor skills. It is therefore worth considering the processes involved in maintaining posture, and how these processes develop.

1.5 Posture and postural control

Posture is defined as the relative position of body parts with respect to a reference frame (Hadders-Algra & Carlberg, 2008). Postural control includes controlling the body's position in space for stabilising or orienting it. Postural orientation is referred to as the ability to maintain a proper relationship between the body segments on one side and between the body and the environment for a task on the other (Horak & Macpherson, 2010).

Postural stability, or balance, is the ability to maintain the centre of mass (COM) within the base of support (BOS). The base of support is the area where the body is in contact with the support surface. The centre of mass (COM) is a point where the body mass is centred. COM is proposed to be the variable maintained by the postural control system. The vertical projection of this point on the BOS is called the centre of gravity (COG). To ensure stability the nervous system produces forces to counteract the COM movement. Centre of pressure (COP) is the centre of the distribution of all forces applied to the supporting surface. To keep the COM within the support base, the COP moves continuously around the COM (Benda et al., 1994; Winter et al., 1991).

Postural control occurs from an interaction of the individual with the task and the environment (Shumway-Cook & Woollacott, 2007). The postural control system, which consists of a complex interaction between the musculoskeletal and neural systems, has the main ability to control our body in space. These musculoskeletal components include joint range of motion, muscle properties, spinal flexibility, and biomechanics of body segments. The neural components include things like motor process, sensory or perceptual process, and the higher level process.

Quiet stance posture is characterised by very little amount of postural sway. There are several factors that affect the stability in quiet stance - the body alignment, the muscle tone, and the postural tone. Perfect body alignment allows the body to keep equilibrium with minimum expenditure of internal energy. This is possible by keeping a hypothetical line going down vertically from the mastoid process to a point just in front of the ankle joint and passing through the knee and hip joints. Muscle tone is another way to stabilise quiet stance. It is the force with which the muscle resists being lengthened. The last factor contributing to stance is the postural tone. Postural control is the increase in antigravity postural muscles to overcome the force of gravity.

There are three postural movement strategies to control disturbed stance; the ankle strategy, the hip strategy, and the stepping strategy (Nashner, 1976). Each strategy depends on the degree of perturbation and disturbance. In case of a small perturbation, the system uses an ankle strategy where the COM is centred on the ankle joint. When the perturbation is larger, the hip strategy is used. It controls the COM movement by producing big and quick motion at the hip joints with concurrent rotation in the ankle joint (Horak & Nashner, 1986). The last strategy is the stepping strategy, where the perturbation is large and can't be controlled by moving the hip alone. The system is trying to keep COM within the BOS and therefore takes a step further to ensure this happens. These movement strategies are used in both a feedback and feedforward control mode. Feedback control is used in response to a sensory feedback (somatosensory, visual, or vestibular). Feedforward control appears when the system anticipates the movement with potential disturbance.

There are different systems involved in postural control; the somatosensory, vestibular, and visual system. The central nervous system (CNS) organises the information from these different sources to determine the body's position in space.

For example, visual inputs provide information of the position and motion of the head with regards to the surrounding objects. The somatosensory system helps maintain our stability by providing the accurate position and motion information of the body with reference to the supporting surface. The vestibular system is an important source of information for postural control. It provides the CNS with information about the head position and movement with regard to the gravity forces.

Postural adjustment strategies are used to maintain body equilibrium and balance (Nashner & McCollum, 1985). Falls caused by postural disturbance are reduced by using anticipatory postural adjustment (APA) or compensatory postural adjustment (CPA). On one hand, APA includes muscle responses or limited body shifts that arise before the postural disturbance. The key role of APA is to minimise the postural disturbance that about to occur and it is mainly based on the previous knowledge and learning (Aruin & Latash, 1995; Li et al., 2007), on the other hand, CPA is a reactionary strategy which is associated with muscle activity and body movements after postural disturbance. This strategy meant to reduce the effect of postural disturbance and are initiated by the sensory feedback signals (Alexandrov et al., 2005; Park et al., 2004).

1.6 Development of postural control

Children develop some vital skills during early years such as crawling, sitting, walking, climbing, and eye-hand coordination in different ways. The evolution of these skills requires the development of postural activity to support the primary movement. Classic theories of development depend on the reflexes while some other recent theories suggest that postural control emerges from a complex interaction between musculoskeletal and neural system (i.e. postural control system).

Several researchers have investigated the postural reflex in the past (Magnus, 1926; Schaltenbrand, 1928). They developed a model based on the reflex-hierarchical theory, which looks at the importance of postural reflexes in motor control. Examining postural reflexes is an important way of identifying motor development delays in children. Attitudinal tonic reflexes; such as asymmetric tonic neck reflex (ATNR), symmetric tonic neck reflex (STNR), and tonic labyrinthine reflex (TLR), are a sign of developmental delays in infants, where the body posture altered when the head position has changed (Milani-Comparetti & Gidoni, 1967). According to the reflex-hierarchical model, the righting reaction considers the position of the head in space and the orientation of the body in relation to the head and surface. These righting reactions are meant to help a person to predict the normal standing position and keep stability when position is altered. There are three main righting reactions that orient the head in space; optical righting reaction, labyrinthine righting reaction, and body-head righting reaction. The other two reflexes that interact with the body position and the surface are neck-on-body righting reaction and body-on-body righting reaction (Cupps et al., 1976).

Balance reactions are important to acquire stability which is vital for meeting developmental milestones. According to the reflex theory, balance develops with a series of equilibrium reactions. These balance reactions are the tilting reaction parachute or protective responses, and staggering reaction. Tilting reaction is used to control the centre of gravity in response to a tilting board. The parachute reaction is used to prevent the body from falling. The staggering reaction mainly appears when a disturbance from the side direction is evident.

More recent theories of motor development, as mentioned previously, consider the interaction between multiple systems in controlling posture. Changes in musculoskeletal system, development of coordination, development of sensory systems, development of sensory strategies of organisation, and development of adaptive and anticipatory mechanisms influence postural development. Balance and postural control development may follow a cephalocaudal sequence or top down approach (Gesell, 1946). Head control is shown to be evident in the first six months of infancy. Some research suggests that neck muscle contraction appears as early as the first month of age (Hedberg et al., 2005, 2004). The development of independent sitting happens after the infant controls the sway in head and trunk. This balance sitting develops during the 6th to 8th month of age (Butterworth & Cicchetti, 1978).

During the process of learning to stand independently, the infant must learn two main things. First, the infant must learn to balance in more challenging situations (standing compared to sitting). Second, the infant must learn to control many new different degrees of freedom (controlling leg and thigh with trunk and head). Thelen and Fisher (1982) suggested that muscle strength is necessary to develop standing balance and walking in infants. On the other hand, Roncesvalles et al., (2001) suggest that infants are capable of producing force beyond their body weight before the development of independent stance. This means that muscle strength is not the main constraint of stance postural control in infant.

1.7 Sensorimotor decision-making

The focus of this thesis is on the topic of how the system decides to choose one action rather than another (sensorimotor decision-making). This topic was neglected in the research for many decades but has more recently become the focus of research interest. For example, Trommershauser et al., (2003b) developed a task where subjects had to reach towards a screen and hit a reward circle within a specific period of time whilst avoiding a penalty circle (Figure 1.3). Subjects knew that landing in the penalty circle would result in a loss of points whilst landing in the reward circle would result in gaining points. This task was formulated in term of statistical decision theory, which tries to capture a simple movement planning task into a decision between different options that is mathematically equivalent to decision-making under risk.

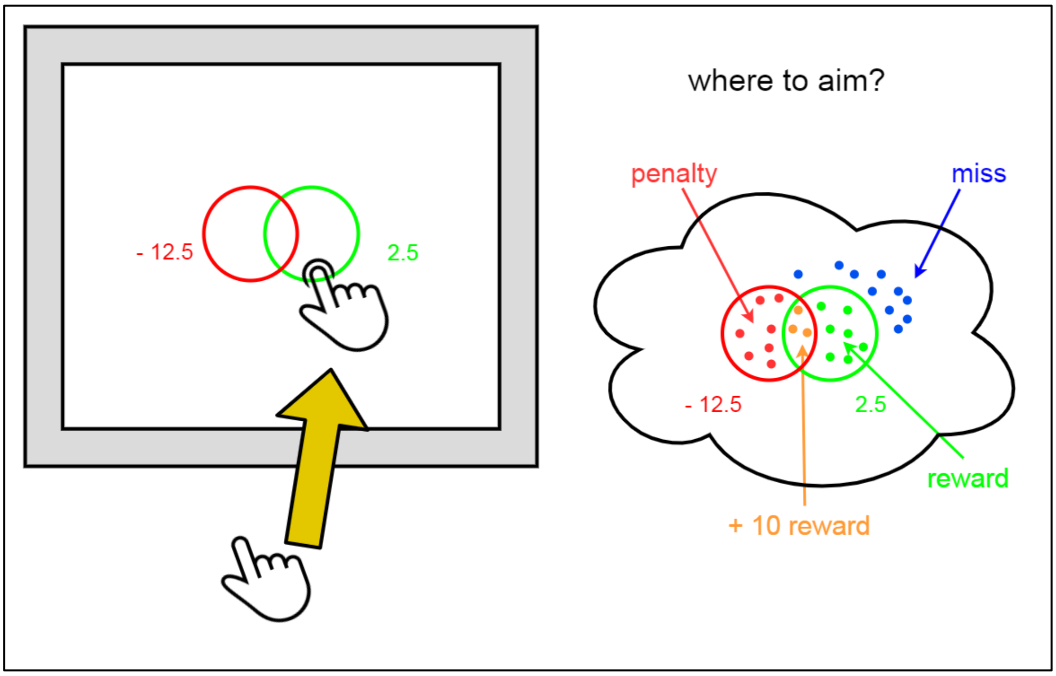

Figure 1.3 Reaching under risk task (adopted from Trommershauser, et al., 2003). On the left hand side the display screen that participants must reach and touch. If the hand landed on the green circle, participants gain 2.5, and if the hand landed on the red circle, 12.5 is deducted. Each circle has a radius of 9 mm.

The experiment allowed Trommershauser et al., (2003) to compare economic decision-making task with an equivalent motor task, and understand the decision-making strategies implemented by subjects. The main question would be where to aim? If subject tries and aims too close to the centre of the reward circle there is high chance landing in the penalty circle, and if subject aims away from the centre of the reward circle to avoid the penalty circle, there is a high probability of missing it. They found that most of the participants used a movement plan that maximises the expected gain. These results reveal fundamental differences between cognitive decisions (which frequently do not maximise expected gain) and sensorimotor decisions.

Neyedli and Welsh (2013) showed that the motor system achieves optimality by optimising the reward gained from the movement (movement outcome not movement execution). They used a similar task to that employed in Trommershauser et al., (2003), and examined the end-point location during an aiming task with external rewards. Participants completed 300 trials aiming at a target overlapped with a penalty area, then a 50 trial interval was analysed separately. Neyedli and Welsh (2013) found that participants learned with time the optimal end-point selection to maximise the gain. At an early stage of the task, the end-point was mainly at the circle centre (suboptimal end-point selection) and this shifted when task experience increased. Another finding was the effect of feedback provided to participants on the performance and decision-making process. The feedback gained after each trial, fail or success, affected the movement variability and end-point selection. Feedback and experience are required for participants to perform the aiming task optimally.

Neyedli and Welsh (2013) presented three possible explanations of the change in the behaviour towards optimality in their task; motor learning factors, probability of hitting the target, and the value of the target. This progression in precision and performance is in consistent with the motor learning literature (H. et al., 2004), and is possibly a result of motor plan accuracy improvement (Schmidt, 1975) or online correction process (Elliott, Digby; Helsen, Werner; Chua, 2001). These early models tends to rely more on the feedforward planning process, and not focused as much on the feedback received from the environment and processed by the system (Gallivan et al., 2018).

The main question when planning a movement under risk (i.e. choosing between a winning or losing option) is how to optimally balance the trade-off between these two options. Maximising the total winning of the movement or the task is important. Two main features of movement that affects the decisions we make and need to be taken into consideration when making motor decision; the cost associated with it and the noise produced by the movement.

Trommershauser, Maloney and Landy's (2003) model tries to answer the question of how the movement should be planned. They considered the movement planning problem as a decision-making problem and developed a model for movement planning based on statistical decision theory (Blackwell & Girshick, 1954). The model has two key concepts; first, the decision maker will include the possible costs associated with movement. These costs can be considered as monetary gain or loss. Second, the decision maker will take into account motor uncertainty when planning movements. Executing a simple task (i.e. reaching for a cup) has multiple movement trajectories which is determined by a movement plan. The motor uncertainty affects the execution of this movement plan effectively which induces a probability distribution on the possible costs associated with the movement. The optimal movement decision is to select a plan that maximise the expected value.

Previous models of movement planning focused mainly on the minimisation of the biomechanical features of the movement by reducing the cost associated. The optimisation goal of such models (as discussed previously) is to minimise some measure of stress on the muscles and joints, for instance; minimising joint mobility (J. F. Soechting & Lacquaniti, 1981), minimising change of acceleration (Flash & Hogan, 1985), minimising torque change (Uno et al., 1989), minimising energy expenditure (Alexander, 1997), and minimising peak work (J. Soechting & Flanders, 1995). However, none of these models can capture human performance related to decision-making tasks that have some cognitive loads (i.e. extrinsic rewards and penalties).

Statistical decision theory (SDT) provides a method for finding the best possible movement plan that would maximise the expected gains (Blackwell & Girshick, 1954). It is a mathematical method of selecting optimal actions under uncertainty and can model a goal-directed movement with motor and sensory uncertainty. The theory consider three components: the state of the world, the sensory information, and the possible actions. There are three functions within the theory. First, there is the likelihood function that links the state of the world to the sensory information (which can be thought of as a function that captures all relevant information to estimate the current state of the world). Second, there is the gain function which determines the gain or loss from a particular action. Finally, there is the decision function which captures the decision-making strategy used by a decision maker.

Statistical decision theory can be used as a mathematical framework to model a simple movement (reach to hit screen). Fundamentally, SDT is used to combine information about uncertainty and gain to achieve the maximisation goals. It is used to explain the decision-making and motor tasks with a common mathematical language (Trommershauser et al., 2003b). This translation can be useful in understanding how the movement could be framed in economic terms, and translating the economic decision-making into a mathematically equivalent motor task. This framework can be used to model different tasks with action and perception components that have gain or loss associated with.

A series of decision-making processes are involved in optimal sensorimotor interactions with the surrounding environment. These processes help someone to decide what movements to execute and when and how to execute them. Thinking of a baseball player task where he/she should follow the approaching ball in order to intercept it in the right time, and another task where he/she needs to decide whether to hit the ball or not. The intercepting task is known as a continuous space task and is the core of sensorimotor control studies, whilst the selection task is known as a discrete space task. The concept of optimisation is central in both; continuous space tasks and discrete space tasks. In the following section, we introduce and review experiments in these two spaces.

The traditional serial models of target selection suggest that movement execution comes after action selection (McClelland, 1979; Miller et al., 1960). However, Cisek et al., (Cisek, 2007) proposed that movement planning and decision-making operate simultaneously. Evidence for this idea was driven by behavioural studies that showed reaching movement trajectories will deviate away from the initially displayed target (Welsh & Elliott, 2004). In neural correlate studies on primates, it has been shown that competing reach targets triggered different sensorimotor areas in the brain before a single target is selected (Cisek & Kalaska, 2005). Therefore selecting and moving toward a specific target might be suggested to occur at the same time, which might imply on the decision-making process used in a simple reaching task.

The main question from these experiments is how the human brain decides between possible actions? On the one hand, there is the goal-based model where a subjective value of the possible actions is computed by integrating different factors (gains, risks, cost, etc.). The brain then prepares an appropriate action plan towards the preferable target (Padoa-Schioppa, 2011). On the other hand, there is an action-based model where the subjective value of possible actions is computed and then multiple actions compete against each other (Cisek, 2006). These findings drive the understanding of decision-making and sensorimotor control interaction.

Previous studies showed that when human make free choices between two possible reaching movements, they are likely to choose the movement that has lowest movement-related cost (Cos et al., 2011, 2012). In another study it was suggested that when choosing between two different actions, the decision-making process evaluates the future biomechanical cost of the possible movement and then select the movement that associated with the lowest cost. Transcranial magnetic stimulation was applied on the motor cortex and showed that the estimation of the effort associated with the possible movements is calculated rapidly and influences the movement decision within 200ms of the object presentation (Cos et al., 2014). These findings suggest that the future biomechanical cost of possible movement is known and the decision-making processes compare between them in order to select the lowest-cost option.

Chen et al., (2018) examined the influence of Pavlovian biases on motor decision-making and whether these biases are reduced with ageing in motor decision-making (as was the case in previous motor performance studies). Choice behaviour was considered in both value dependent and value-independent processes. An app-based motor decision task examined subject's behaviour towards gaining and losing points when making go/no-go decisions. The game require subjects to execute a tapping movement on a predefined path and trajectory within a limited timeframe. The subject had to decide before taking the actions whether to take the motor gamble (the risk) or skip the trial. There were reward and punishment combinations for each trial, and subjects started with 250 points and needed to collect as many points as possible. Chen et al., (2018) tested 26,532 participants with the age varying from 18 years to more than 70 years old and an additional 120 participants were recruited for an experiment on the estimation of motor performance. Older adults collected fewer points compared to the younger adults. Points collected depended on two factors; motor performance and the decision made. Smaller screen size, smaller target size and older age were factors that were found to be associated with the reduction in motor performance (i.e. success rate). Older adults moved slower than younger adults and therefore when the task was more difficult they failed more often. To test the assumption that participants had good estimates about their success probability, participants were asked to estimate their probability of success and then execute the motor part of the task (i.e. without doing the decision-making part). The probability of motor success was estimated accurately by participants within the different age group. Participants showed less risky behaviour (decreased gamble selection) with age in reward trials, and less in the punishment trials. Age-related changes in the two trial types (i.e. reward and punishment) for both value-dependent and value-independent parameters were found. Similar decision-making tendencies were found across motor and economic domains. Low risk aversion in the value-dependent process indicated that risk aversion was present in reward trials and risk seeking in punishment trials. The risk preference parameter was reduced with age suggesting that older adults increase value-dependent biases (which means more risk aversion in reward and more risk seeking in punishment trials).

1.8 Cognitive vs sensorimotor decisions

The production of the high-level skills observed in humans requires both the motor and cognitive systems to work together. According to Fitts and Posner (1967), motor learning has three phases; the cognitive phase (memorising the movement sequence); the associative phase (linking the parts into one smooth action) and the automatic phase. In three experiments that aimed to study sequence learning ability, Raw and colleagues (2019) compared young and older adult movement performance in a sequence learning task. In the first experiment, participants used a tablet PC and standard computer mouse to learn a movement sequence between targets located in the screen. The number of correct recalls and the recall movement time were measured for older and younger adults. The results show that participants with different age groups learned and recalled the movement sequence over test trials (14 trials). In another experiment, participants completed the same task as the previous experiment but comparing the preferred and non-preferred hand performance. Similar improvement in sequence recalling was evident as the previous experiment but especially for the younger adults and the preferred hand condition. The movement time was faster for the younger adults and when using the preferred hand compared to older adults and the non-preferred hand. The final experiment used the same sequence learning task but with two different conditions that varied the motor demands. In the first condition the mouse used in natural place (on a desk) whilst the other condition the mouse used in a rotated position (against an inverted T-shape stand). The learning sequence was reduced with tht sideway orientation compared to the regular orientation indicated by lower number of recalls and slower movement time.

In the dual-task literature, the cognitive system and motor system are presented as two separate systems that interfere with each other. Raw and colleagues (2019) introduced the Cognition Action Interaction Theory (CAIT) to capture the idea that most activities of daily living require both the motor and cognitive system to operate in an interactive manner. It recognises that cognitive and motor systems are different systems and can be studied separately whilst conceptualising them as mutually dependent systems. The CAIT suggests that increasing the motor elements in a sequence learning task will lead to reduction in the cognitive elements and thereby limit learning rate. The results presented in Raw et al., (2019) showed that the cognitive and motor systems play an interacting role in skill learning, and this observation could expand to decision-making tasks. This thesis therefore studied the way in which sensorimotor costs and extrinsic (cognitive) rewards interact to determine which action is selected.

1.9 The use of Virtual Reality in research

Virtual reality (VR) systems are opening windows and new opportunities for science and research. Behavioural research is one of the fields that benefit from the advancement in the software and hardware in VR. The concept of VR started in the sixties when Sutherland described VR like a window that user perceive the virtual world as real (Sutherland, 1965). Since then different definition of VR was presented, for instance Fuchs and Bishop (1992) defined VR as "real-time interactive graphics with 3D models, combined with a display technology that gives the user the immersion in the model word and direct manipulation" (Fuchs and Bishop, 1992, p. 156). On the other hand VR described as "The illusion of participation in a synthetic environment rather than external observation of such an environment. VR relies on a 3D, stereoscopic head-tracker displays, hand/body tracking and binaural sound. VR is an immersive, multi-sensory experience" (Gigante, 1993, p. 4).

Three main features that emerged from the VR system definitions such as; immersion in an environment, interaction with an environment, and perception of an environment. The immersion feature is concerned with the number of senses stimulated, the interactions with the virtual environment, and the similarity to reality in the stimuli used in the virtual environment. The level of immersion might vary and depends on the technological system used (Slater, 2009). There are three types of immersion in VR systems; (i) non-immersive systems which use the desktop to provide the image of the world, (ii) semi-immersive systems which produce a stereo image of a three dimensional (3D) pictures presented on a monitor, and (iii) full-immersive systems which give a full simulated experience by using the head-mounted display (HMD) for increasing the stereoscopic view of the environment through head movement in addition to haptic and audio devices.

The usr of virtual reality systems is wide and varys from gaming (Meldrum et al., 2012; Zyda, 2005) to military training (Alexander et al., 2017), to education (Englund et al., 2017), and psychological treatment (Freeman et al., 2017; Neri et al., 2017). The ability to present the stimuli in scientific research with high realism in VR allows the researchers to implement this technology in different fienlds such as psychological research related to phobia and pain adaptation or motor rehabilitation (Botella et al., 2017; Llorens Rodríguez et al., 2014).

1.10 Overview of the thesis

The body of experimental work presented in this thesis focuses on the interaction between the sensorimotor system and the cognitive system when making decisions. Many factors could contribute and bias the decision-making process in a task with both cognitive reward and sensorimotor cost, for instance; level of cost, value of reward, gender of the participant, noise in motor or sensory system, and age group. The key research question within this thesis was whether or not the sensorimotor cost and cognitive reward interact in different decision-making processes. Another aim of this thesis was to identify and examine possible biases that influence the decision-making processes.

The first experimental chapter of this thesis investigated the way that extrinsic 'cognitive' rewards and sensorimotor costs interact in decision-making processes. This experiment also explored whether there are gender differences in the ways that participants combine extrinsic rewards and sensorimotor costs. There is a large body of literature that suggests females show less risk taking behaviour compared to males (Bruce & Johnson, 1996; C. Harris et al., 2006; Powell & Ansic, 1997). These differences in risk aversion are shown in a number of different ways within real world settings: females rate risk more highly than males in a variety of scenarios including: driving, fire, crime, food safety and medical surgery (Breakwell, 2014). It seemed reasonable, therefore, to hypothesies that there might be gender differences in the way that our participants behaved in response to the extrinsic rewards and sensorimotor costs within our task.

The second experimental chapter explores the impact of increasing motor noise on the way that participants choose which action to select. Noise is defined as random or unpredictable fluctuations and disturbances that are not part of a signal (Faisal et al., 2008). Noise occurs at every level of the nervous system and cause a main problem for information processing. These levels vary from the perception of sensory information to the generation of motor activities. The main goal of the brain is to receive and process information. There are different stages in the nervous system where noise is presented; cellular noise, sensory noise and motor noise. In this experiment, participants used their non-preferred hand to execute actions and make decisions. Our experimental design was such that the expected value of the targets did not change as a function of the noise manipulation (because the length of time that the targets were present took into account the fact that the additional noise caused an increase in movement duration). This meant that the experiment allowed us to explore whether participants were tuned to the actual sensorimotor costs or whether the action selection process would be affected because of a higher level awareness of the task being more difficult.

The third experimental chapter added another type of noise, sensory noise, where participants couldn't follow the online visual feedback of their hands. The rationale for this experiment was identical to the hypothesis testing within the second experimental chapter – but was focussed on whether perceptual noise rather than motor noise per se affected the decision-making process.

In the fourth experimental chapter, the effect of repeating the task over period of time on the decision-making process was examined. This chapter was motivated by an analysis of the data across all the participants in the first three experiments. These data allowed identification of factors that biased the decision-making process. These biases could be captured using a Partially Observable Markov Decision Process model. The pom-dp model predicted that the participants should increase the extent to which they selected the 'risky' option in the experimental task.

The fifth experimental chapter was concerned with the effect of reward and cost manipulation within participant. This design allowed us to explore the extent to which participants traded off exploration and exploitation when choosing one action over another. There are three possible models to address the problem of how to trade-off between exploration and exploitation in unstable environment (Daw et al., 2006). On the first model, a simple decision rule was used where the subject remembers the expected value for each alternative based on their previous experience. Usually the decision maker chooses the option with the greatest value (exploitation) however sometimes, with a fixed probability, the decision maker choose randomly among the other alternatives (exploration). This model usually called “greedy”; where the decision maker chose the greedy alternative that believed to be best. For the second model, alternatives are chosen with probability weighted by their estimated values. The decision maker in this model prefer the option with a higher value, however this behaviour is reduced by the value of the alternative options and the noise added to the decision maker. Therefore the balance between exploration and exploitation is maintained by relative value of alternatives and the gains. With higher gain, decisions are determined more by relative value (exploitation), but with lower gain those decisions are evenly distributed at random (exploration). In the last model, the choices are made similarly to the previous model but adding “uncertainty bonus” to the alternatives that have not been selected. This bonus would promote the probability of the unchosen alternative (i.e. exploration) (Daw et al., 2006).

The final experimental chapter investigated differences between age groups in decision-making and action execution. It has been found that children as young as three to six years old can differentiate between low value and high value options (Davidow et al., 2018). Children’s and adolescence’s selective attention was compared with young adults and the results showed that young adults consistently responded more to high value targets compared to low value. Younger adults also responded faster to the high value targets compared to the adolescents and children. It has been found that younger children (4 to 5 years) make use of reward in improving their performance in a developmentally appropriate task. However, this reward influence on performance was limited when the task complexity increased. When cognitive task difficulty is similar to the subject's ability, children, adolescents, and adults improved their control performance for rewarding outcome when compared to a neutral outcomes. Adolescents can make use of value in simple tasks but the importance of value in action execution is limited in a more difficult tasks. Adults and adolescents showed similar accuracy in value dependent learning. These observations were challenged when the task has greater learning demands (i.e. increased number of objects to learn, reduce reinforcement probability, or increased feedback complexity). Adolescents showed lower accuracy level in complex learning tasks compared to adults. Moreover, they learned the task without feedback integration which might suggest that adolescents learn better in less complex environments.

Davidow et al., (2018) found that children were similar to adults and showed faster motor response to cues that linked to higher values. One limitation in these kind of studies is that monetary evaluation is different across development. Previous research has found that adolescents and adults judge money similarly. Some research has demonstrated that adults improve their goal-directed actions selectively when high value goals are at stake. When looking at younger adults, they are more likely to improve their control when acting upon high value targets compared to a low value targets. Cognitive control improves from childhood to adolescence but cognitive control in adolescence is undergoing continuous development and changes when compared to adults in challenging scenarios with difficult task demands. These developments are correlated with the functional development of the brain systems (e.g. prefrontal cortex and parietal cortex).

These observations in adolescence suggest that the recruitment of control systems in the brain becomes more stable and strategic and therefore performance is improved.

CHAPTER 2: Task development and piloting work

2.1 Introduction

Using immersive technology is becoming more common in research as the investment in hardware and software increased. Virtual reality (VR) has already been used in different areas of research including; rehabilitation (Adamovich et al., 2009), medical surgery (Gurusamy et al., 2008), and sport training (Gray, 2019; Neumann et al., 2018). In set of experiments, Harris et al., (2019) used VR golf putting simulation to examine the physical and psychological fidelity. The golf putting performance was compared between novice and expert participants and found that simulation was able to recognise the experts and novice participants. In another research, Hasan et al., (2020) used VR system to examine object-reaching behaviour in cluttered environment and compared the data collected from VR with robots.

This chapter includes the piloting work involved in the task development and the general methodology of the experiments carried out. In order to develop the task and to test all possible alterations and variables, four pilot studies were carried out. A total of 33 participants aged 18 to 29 years helped to finalise and develop the task. The aim of this piloting work was to come with a final task that would capture the reward and cost in sensorimotor decision making. The final task should have some element of difficulty so it is not easy to execute, measures the decision making skills, and does not take long time to complete.

2.2 Materials and apparatus

The Oculus Rift (CV 1) Virtual Reality (VR) system was used to collect the data. The Oculus Rift comprised a head-mounted display (HMD), two controllers and two sensors. A gaming-grade laptop (ASUS ROG GL 502VM, Intel Core i5-7300HQ, Nvidia GTX 1060) was used to run the Oculus Rift. The HMD was first calibrated using the built-in procedure, which set the virtual floor level to match the physical floor. The virtual environment was an empty room with a 3m height, 6m width, and 6m depth (Figure 2.1**Error! Reference source not found.**).

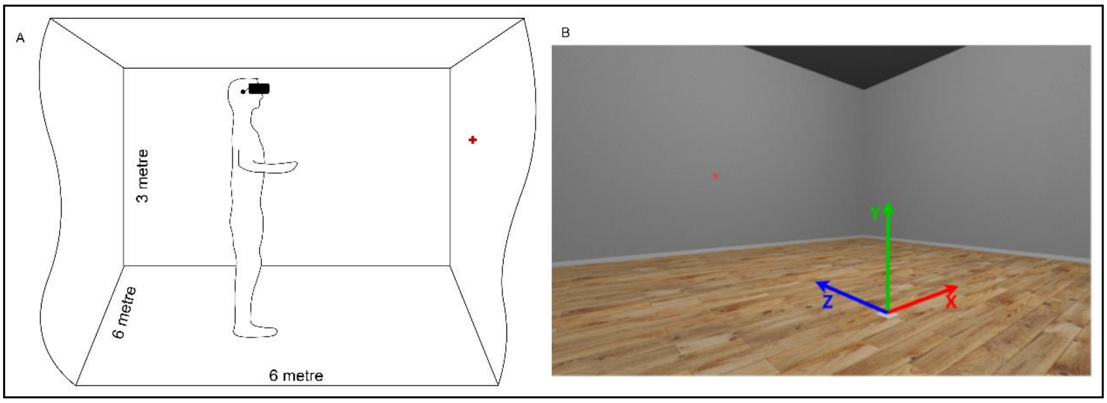

Figure 2.1 Panel A shows a schematic of a participant wearing the head-mounted display with red cross and the dimensions of the virtual room; 3m height, 6m width, and 6m depth. Panel B shows the virtual room from participant's prospective with the red cross, dimensions, and a white spot where the participant stood.

2.3 First pilot to examine the Go/No-Go design in decision-making

The first pilot assessed the GO/No-Go procedure in decision-making using the virual reality. The primary idea was to present participant with a target and allow them to either reach (Go) or skip (No-Go). It involved five postgraduate researchers (three males and two females) aged from 24 to 29 years old. The aim of this pilot was to examine that the design is effective and captures the decision making behaviour. There were three sessions in this pilot; practice session, baseline session, and decision-making session.

2.3.1 Practice session

In the practice session, the participants held the controller on the starting target (red bubble) and waited until it change colour. The target (white bubble) appeared in front of the participants and then the starting target turns into green which indicates that participants must reach to the target. Then the participants need to reach to the target and pop it. In this session, the participants saw one target per trial and it appeared on three different distances (0.50 arm’s span, 0.57 arm’s span, and 0.65 arm’s span). They reached four times per target distance in quasirandom order (total of 12 trials) to familiarise themselves with the task.

2.3.2 Baseline session

In the baseline session, the participants held the controller on the starting target (red bubble) and waited until it change colour. The target (white bubble) appeared in front of the participants and then the starting target turned into a green which indicates that participants must reach to the target. In this session, the participants introduced with one target per trial without reward (stars). This target appeared on three different distances (0.50 arm’s span, 0.57 arm’s span, and 0.65 arm’s span). The participants needed to reach to the target as fast as possible to measure their movement time. The median movement time was calculated and used in the decision-making session as a bubble appearance time. The participants were introduced with a feedback message “Please pop the bubble as fast as you can” and told verbally by the experimenter to reach as fast as possible for each trial. The participants reached eight times for each target distance in a quasirandom order (total of 24 trials).

2.3.3 Decision-making session

The last session is the decision-making session, where the participants needed to decide whether to reach to the target or not (Go/No-Go). Similar to the previous sessions, the participants held the controller on the starting target (red bubble) and wait until it change colour. The target (white bubble) appeared in front of the participants and then the starting target turns into a green which indicates that a decision must be made. The decision in this pilot was either to move the controller and reach to the target or keep the controller at the starting target (red bubble). The target appearance time depends on the participants' movement time in the baseline session. The median movement time was calculated for each target distance from the participants' performance in the baseline session. Should the participants decided to reach to the target, the controller must be moved toward it and haptic feedback (vibration) felt when the target is hit.

A screen with feedback of the trial outcome appeared in front of the participants to indicate whether the target was missed "Too slow!" or hit "Bubble popped!". The feedback colour when the participants hit the target is blue and when miss the target is red. These different colours were used to emphasise the visual feedback difference between the two trial outcomes. There are three outcomes for each trial in this pilot; hit when the participants reached to the target and hit it on time, miss when the participants reached to the target but didn't hit on time, and the last outcome was no go should the participants decided not to reach at all and instead kept the controller on the starting target (red bubble). The participants reached 16 times for each target distance in a quasirandom order (total of 48 trials).

2.3.4 First pilot results

Observing the participant's behaviour in this pilot gave a clear idea about this design. The participants reached most of the time toward the target regardless of their outcome and the target distance. The participants hit the target around 75% of the time while miss the target around 25% of the time (Figure 2.2).

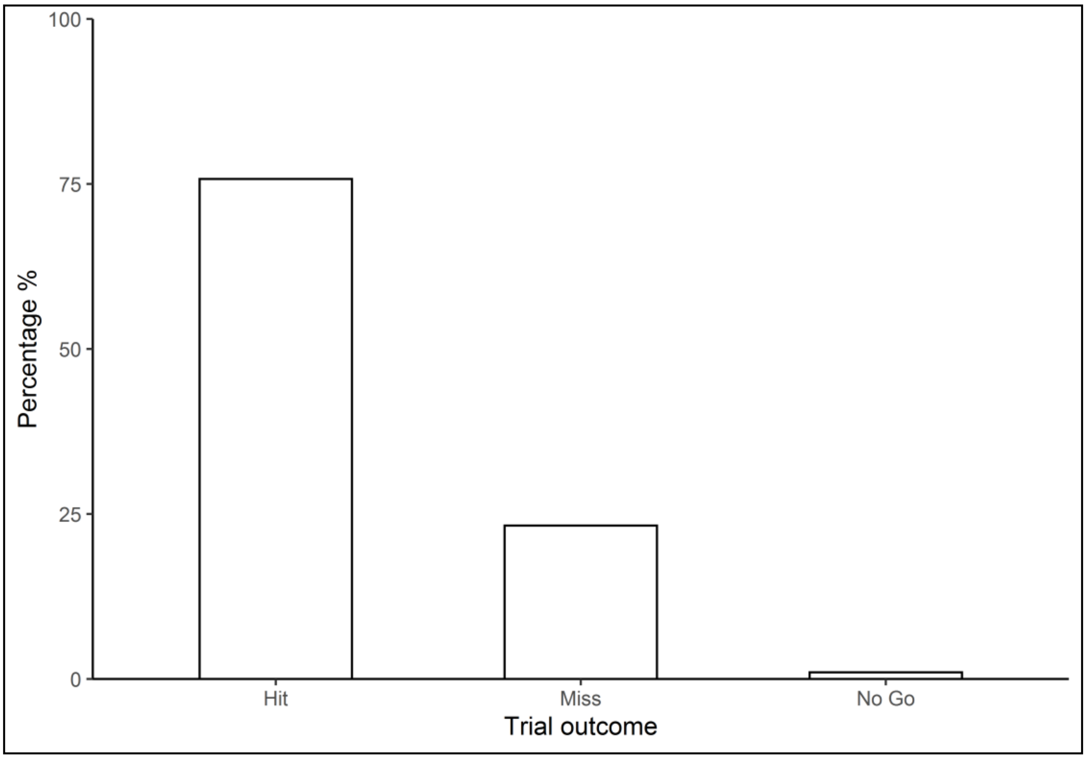

Figure 2.2 The selection in the first pilot. Around 75% of the time they hit the target and around 25% they miss the target.

As participants have only one target to reach for, the participants had the feeling of the need to reach when the starting target went green. This might be attributed to the time given to make the decision or it was a reactive behaviour rather than a decision making. Therefore, the second pilot was designed to eliminate these two factors as shown below.

2.4 Second pilot to examine the two choice decision-making design

In the second pilot, the target appearance design was manipulated to allow more time and to facilitate the decision-making process. Compared to the previous pilot, another target was introduced (fixed target) in addition to the main target (disappearing target). The main difference was in the decision-making session where two targets appeared instead of one, more details of this session below. The other two sessions (practice and baseline) were the same as the first pilot. Nine postgraduate researchers recruited in this pilot (two males and seven females) with an age ranged from 24 to 29 years old.

2.4.1 Decision-making session

In the decision-making session, participants chose between two targets. They held the controller on the starting target (red bubble) and waited until it change colour. As mentioned earlier, the participants were introduced with two targets (white targets); fixed target and disappearing target. There were four differences between the fixed target and disappearing target. First, the fixed target distance always appeared at 0.35 arm's span while the disappearing target appeared in three different distances (0.50 arm's span, 0.57 arm's span, and 0.65 arm's span). Second, the fixed target appeared randomly in the opposite direction to the disappearing target (right vs left). Third, the value of the reward each target has. The fixed target always has one star reward while the disappearing target has two stars of reward. The last difference was the appearance time, the fixed target appeared for longer time compared to the disappearing target. The appearance time for both targets depends on the median movement time of each participant in the baseline session.

When the target appeared in front of the participants, participants waited for the starting target to change colour to green, which indicates that a decision must be made. Then the participants moved the controller toward one of the targets; the fixed target or the disappearing target. Should the participants decided to reach to the target, they move the controller towards it and haptic feedback (vibration) felt when the target is hit. A screen with feedback of the trial outcome appeared in front of the participants to indicate whether the target is missed “Too slow!” or hit “Bubble popped!”. The feedback colour when the target is hit was blue and when the target is missed was red. These different colours were used to emphasise the visual feedback difference between the two trial outcomes.

There were four trial outcomes in this pilot; high reward hit when the participants reach for the disappearing target and hit it on time, miss when the participants reach for the disappearing target and don’t hit it on time, low reward hit when the participants reach for the fixed target and hit it, no go when the participants didn’t move the controller from the starting target (Figure 2.3). The participants reached 16 times for each target distance in a quasirandom order (total of 48 trials).

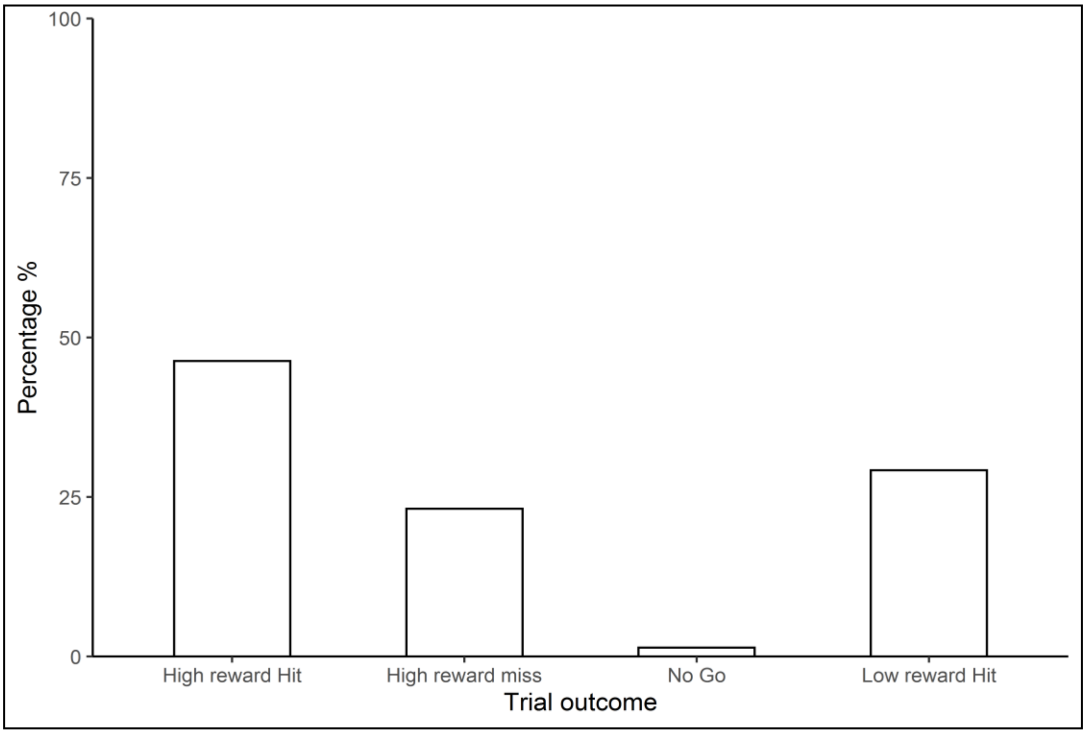

Figure 2.3 The selection percentage in the second pilot as a function of the trial outcome.

2.4.2 Second pilot results

In this pilot, the participants showed different behaviour compared to the previous pilot. Participants showed risky behaviour (i.e. reaching for the disappearing target more often compared to the fixed target). Participants reached to the disappearing target (risky choice) more often regardless of the target distance. Figure 2.5 shows the selection percentage for each target distance.

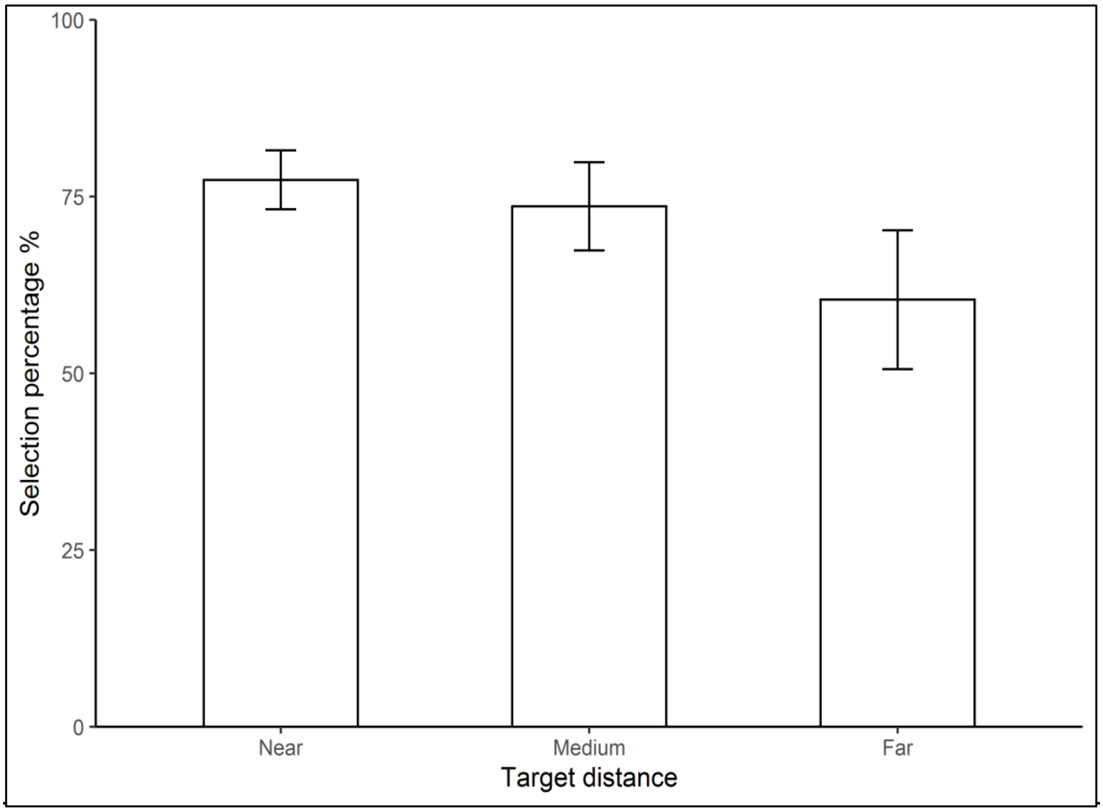

Figure 2.4 The mean selection percentage in the second pilot as a function of target distance with standard error bars.

The hit rate is high for all the target distances which means that the participants reached most of the time to the disappearing target (the risky choice) and hit the target. Figure 2.5 shows the hit for each target distance.

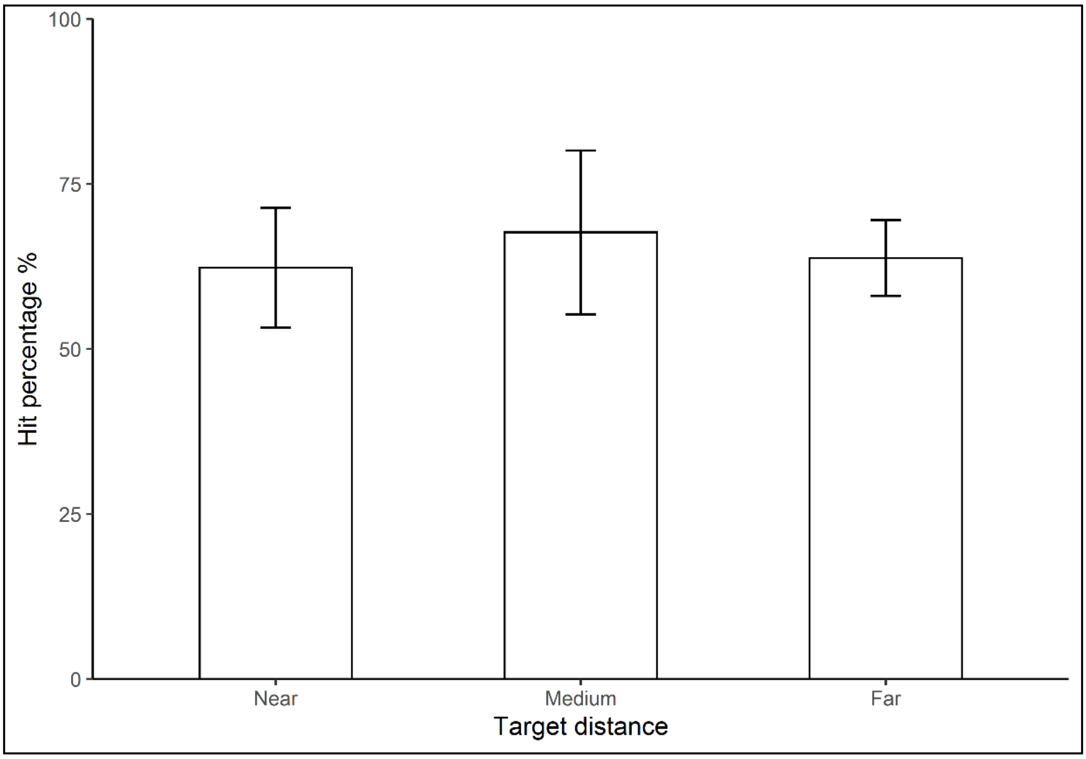

Figure 2.5 The mean hit percentage in the second pilot as a function of target distance with standard error bars.

The noticed decision-making behaviour might be attributed to the target distance. The target distances used might not be hard (far) enough, so participants reached and hit the target (regardless of the distance) all the time. The next pilot tested this idea and made the target appears further.

2.5 Third pilot to examine the target distance effect on decision-making

In the third pilot we examined the target distance effect on the decision-making behaviour. After the results from the previous pilot, in this pilot we changed the target distance in the decision-making session as explained in the next section. Ten psychology undergraduate students were recruited in this pilot (four males and six females) aged from 18 to 23 years. Similar to the previous pilot, this pilot has three sessions (practice session, baseline session, and the decision-making session). The only difference was in the target distances, which became 0.50 arm’s span, 0.65 arm’s span, and 0.75 arm’s span in all sessions.

2.5.1 Decision-making session

In the decision-making session, participants chose between two targets. Similar to the previous pilot procedure, the only difference in this pilot was the disappearing target distance. The disappearing target appeared in three different distances (0.50 arm’s span, 0.65 arm’s span, and 0.75 arm’s span). There were four trial outcomes in this pilot, Figure 2.6 shows the percentage of each outcome.

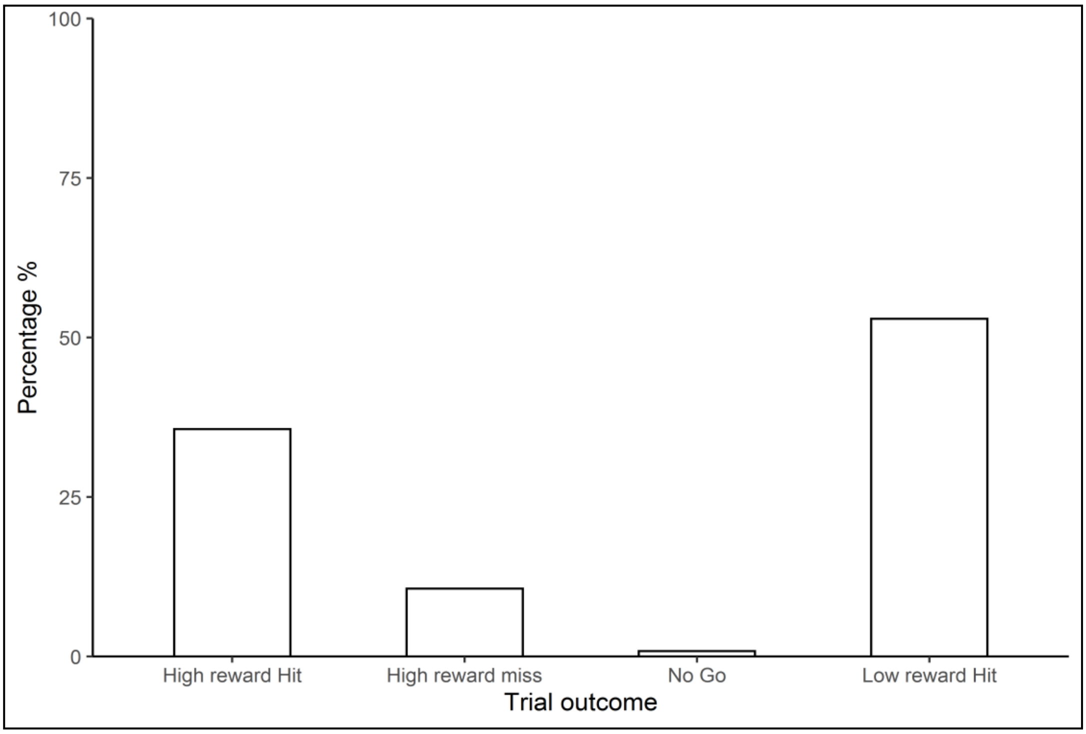

Figure 2.6 The selection percentage in the third pilot as a function of the trial outcome.

2.5.2 Third pilot results

The results from this pilot were closer to what we aimed for. Figure 2.7 shows the riskiness behaviour shift from risk-seeking (i.e. reaching to the disappearing target) to risk-averse (i.e. reaching to the fixed target) when the target appears at far distance compared to the near distance. The participants reached for the further target (0.75 arm's span), however, hit it less frequently compared to the other target distances (0.5 arm's span and 0.65 arm's span). This allows us to conclude that the 0.75 arm's span target is within reach distance for the participants but not too easy to hit in every attempt.

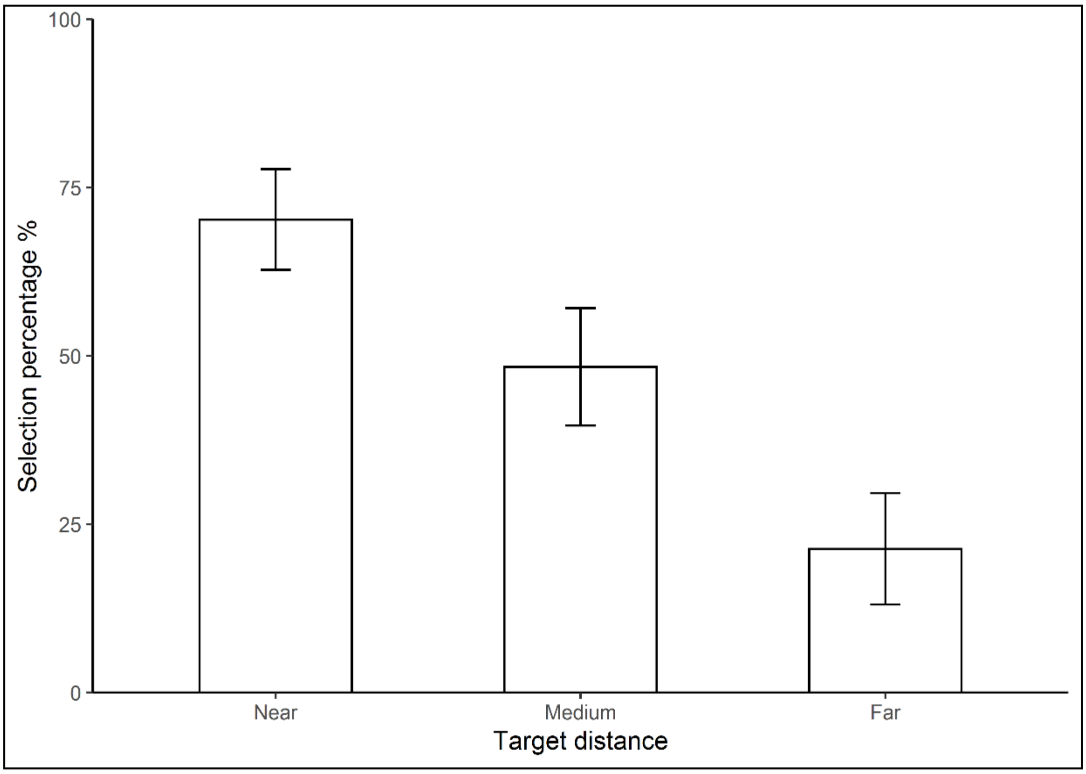

Figure 2.7 The mean selection percentage in the third pilot as a function of target distance with standard error bars.

When looking at the riskiness behaviour of participants, we notice that the trend is affected by the target distance. The further the target the safer the behaviour noticed from participants. The hit rate for different target distances differs from the previous pilot as shown in Figure 2.8. The observed results gives an evidence that the target distances used in this pilot is acceptable and helping to capture the main aim of the intended experimental body. Therefore, these target distance were used for the upcoming experiments.

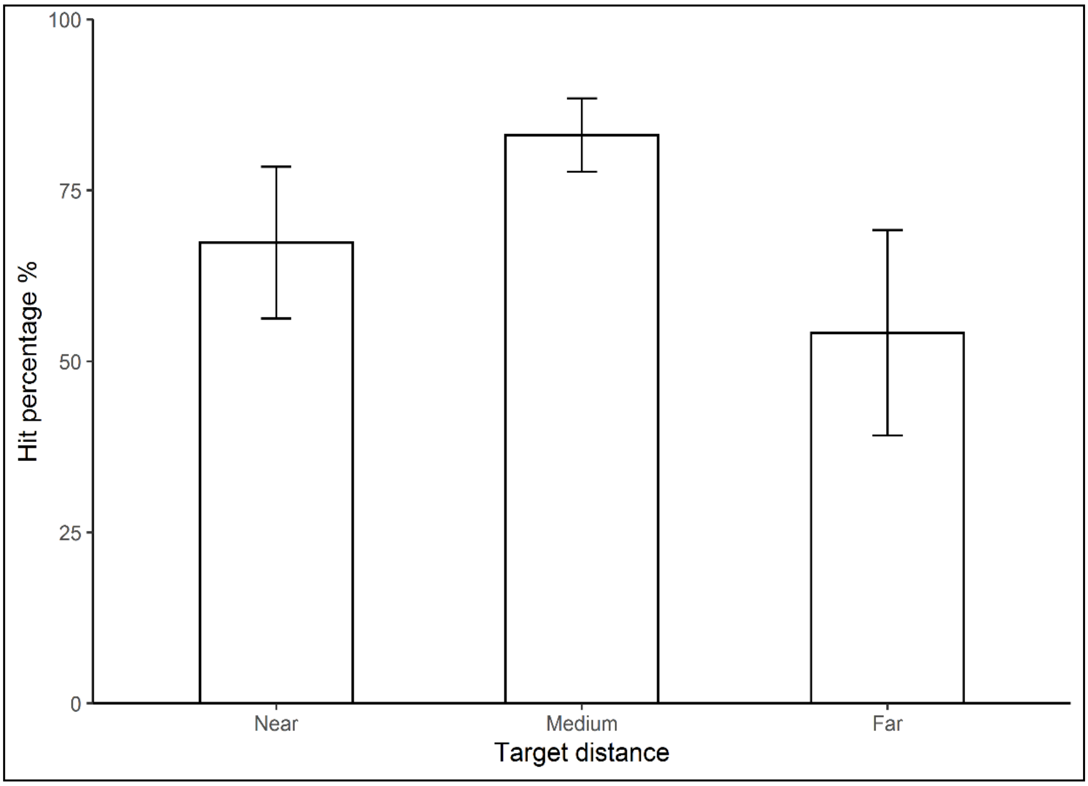

Figure 2.8 The mean hit percentage in the third pilot as a function of target distance with standard error bars.

In the previous pilots the targets were presented randomally (left vs right). A question worth investigating was wether or not the appearance randomisation would play a role in the decision-making process. The next pilot trys to answer this question.

2.6 Fourth pilot to examine the randomisation effect on decision-making

To examine the appearance order effect, nine undergraduate students from the school of psychology (eight females and one male) were recruited with an age ranged from 18 to 23 years. The design was similar to the previous pilots, however the appearance order of the target was changed. The target appearance was in pseudorandom order to examine the difference between this order appearance and the random appearance. The practice and baseline sessions were similar to the previous pilot, however the baseline trials increased in this pilot compared to the previous pilot (27 trials) to get better median movement calculations. The median has been used over the mean to make sure the movement time is not affected by the skewed data.

2.6.1 Decision-making session

In the decision-making session, participants chose between two targets. Similar to the previous pilot procedure, the only difference was the target appearance order. The pseudorandom target order was fixed per participant with three trials in the right direction and the consecutive three trials appeared on the left direction. There were five trial outcomes in this pilot; hit when the participants reach for the disappearing target and hit it on time, miss when participants reach for the disappearing target and don't hit it on time, low reward hit when the participants reach for the fixed target and hit it, no go when the participants didn't move the controller from the starting target, and the last outcome is premature where the experimenter failed the participants trial because of stepping out the white circle (Figure 2.9). Participants reached 16 times for each target distance in a quasirandom order (total of 48 trials).

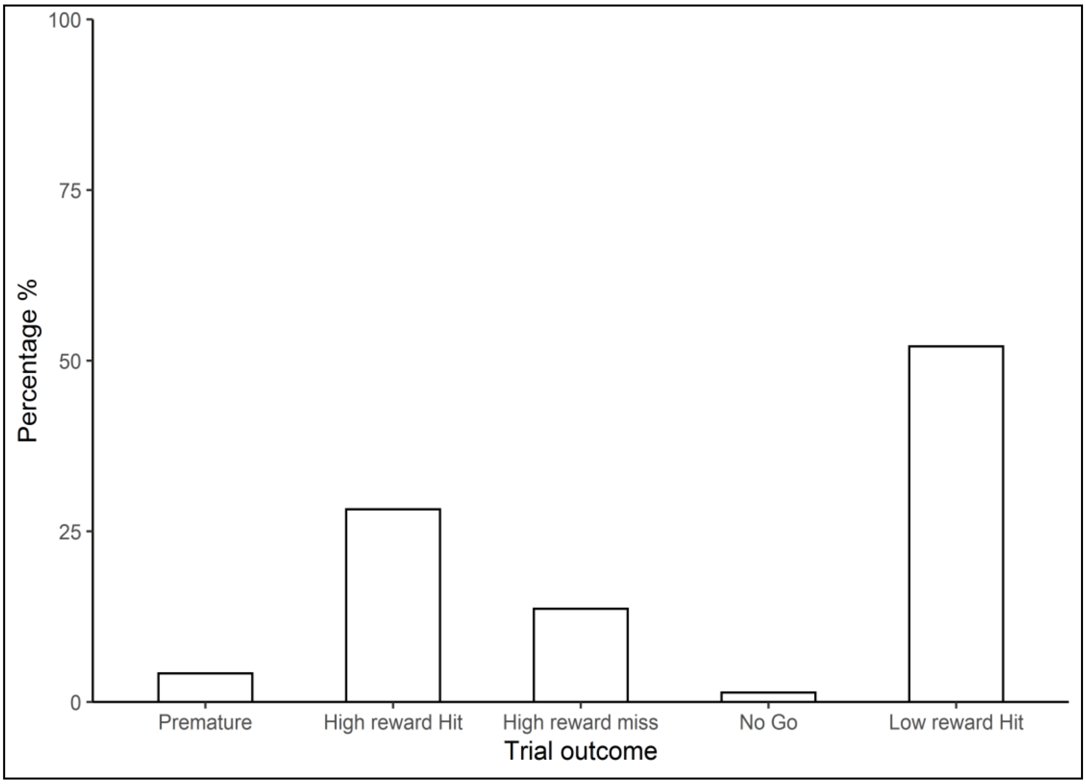

Figure 2.9 Participants selection percentage in the fourth pilot as a function of the trial outcome.

2.6.2 Fourth pilot results

The target appearance order effect was tested in this pilot. There was no order effect on the participants' behaviour between the two appearance orders examined. Therefore, the random order was the best design to carry out applying in the experiment. The results from this pilot were closer to what we aimed for. Figure 2.10 shows the riskiness behaviour shift from risk-seeking (i.e. reaching to the disappearing target) to risk-averse (i.e. reaching to the fixed target). Participants reached for the further target (0.75 arm's span), however, hit it less frequently compared to the other target distances (0.50 arm's span and 0.65 arm's span). This allows us to conclude that the 0.75 arm's span target is within reach distance for the participants but not too easy to hit in every attempt.

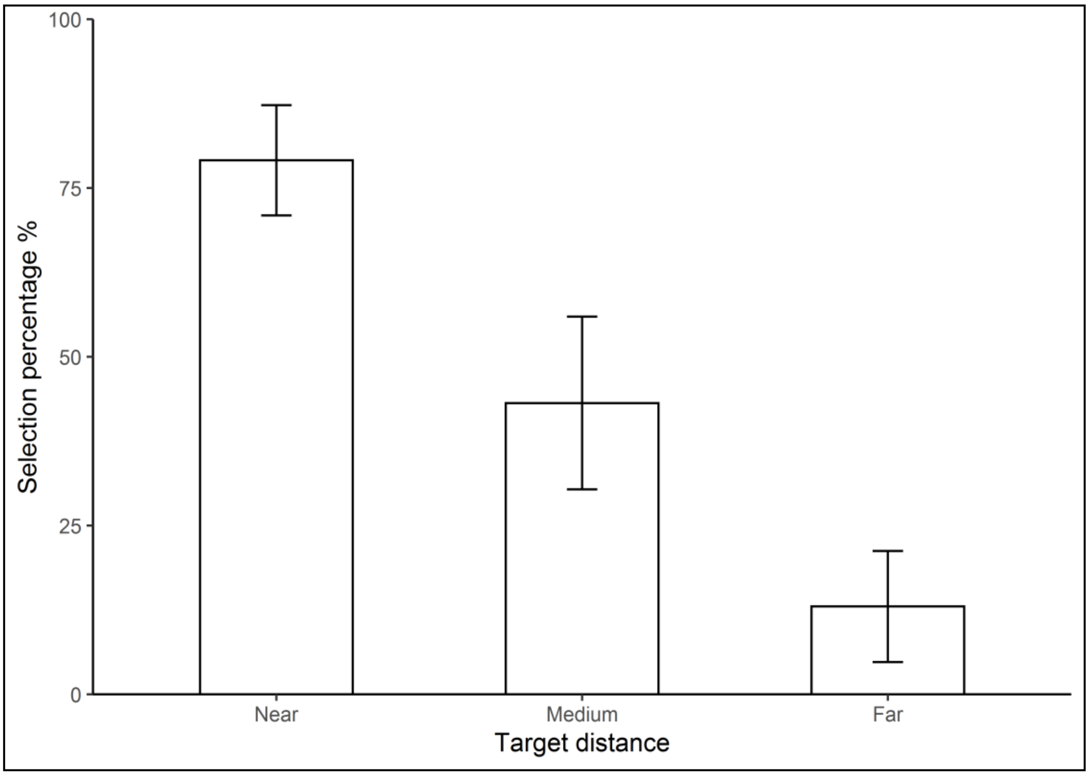

Figure 2.10 The mean selection percentage in the fourth pilot as a function of target distance with standard error bars.

When looking at the riskiness behaviour of participants, we notice that the trend is affected by the target distance. The further the target the safer the behaviour noticed from the participants (Figure 2.11).

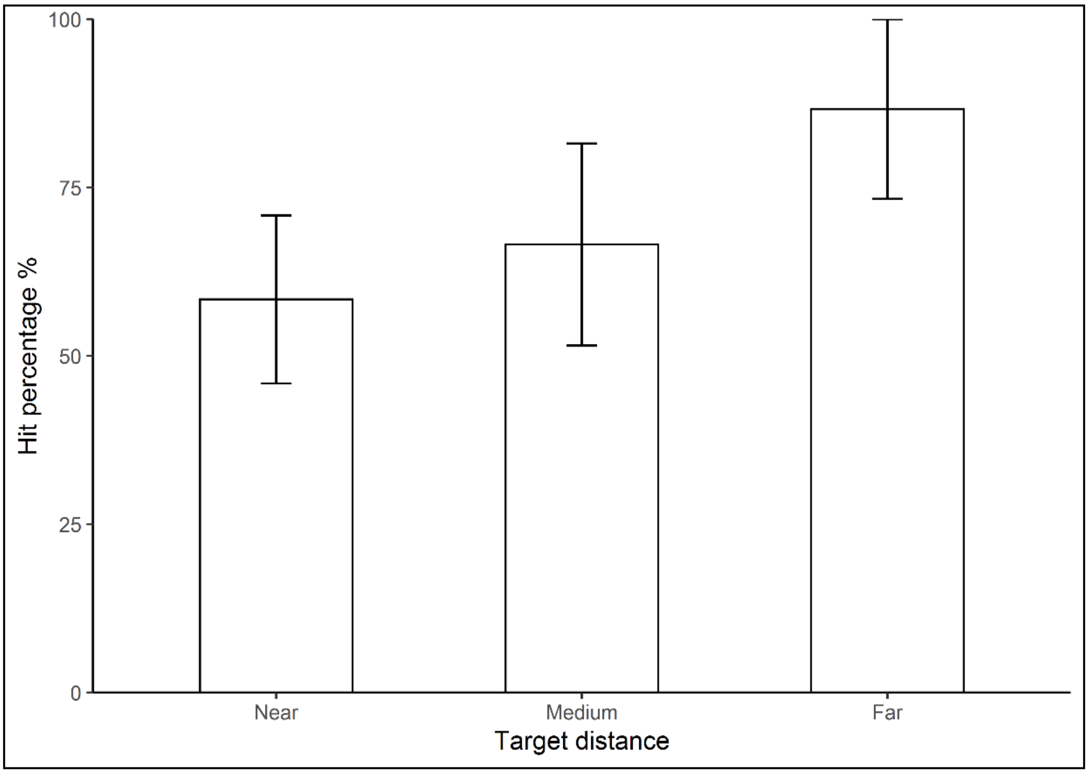

Figure 2.11 The mean hit percentage in the fourth pilot as a function of target distance with standard error bars.

After the pilot work carried out, the final design is presented in the next section with a general methods explained for the different experiment.

2.7 General methods

The previous four pilots help to develop the task used in the different experiment presented in this thesis. This general method section presenting the main features and layout of the task that was in different experiments.

2.7.1 Baseline data

First, participants' age, preferred hand, height, and arm span were measured (panel C in Figure 2.12). The University of Leeds Ethics and Research Committee approved this study and participants gave their written, informed consent. They stood on a dedicated spot on the floor with their feet shoulder width apart. Height was measured by calculating the distance between the VR headset and the physical floor. Arm span was measured by asking the participants to hold two controllers (one in each hand) and spread their arms horizontally and the distance between the two controllers was recorded.

Three measures of postural stability were taken (eyes open, eyes closed, and oscillating room) by measuring the movement of the Oculus headset. The location of HMD in the virtual room was recorded at a frequency of 90 Hz. The postural stability was measured by computing the path length (sum of all point to point distance over time). In the *eyes open* condition, participants were asked to fixate a red cross placed on the wall in the virtual room for 10 seconds. In the *eyes closed* condition, the virtual room was turned to black and participants were asked to close their eyes while maintaining their posture for 10 seconds. In the *oscillating room* condition, participants kept their eyes open and were instructed to remain stable for 10 seconds while the room moved forward and backward on an amplitude of 5° and rate of 0.25 Hz. The postural stability data were removed from the experimental chapters analysis because the results were not informative.

2.7.2 General task structure

Participants undertook three sessions: a practice session, a baseline session, and a decision-making session, and took seven minutes on average to complete the task. In the practice session, participants were provided with a visible target that appeared at one of three distances: 0.50, 0.65, and 0.75 arm span from the start position. The participant’s objective was to move a controller held in the hand to hit the target. The target remained visible until the participants hit it successfully.

In order to complete a trial, participants first moved the controller to a starting position (a red bubble) that was located on the midline at a height equivalent to 0.75 of the participant's height and at a distance of 0.20 arm's span. The red bubble then turned to amber. There was a randomly generated inter-stimulus interval of 750 to 1500ms after which the target appeared. Following a further interval of 300 to 500ms (allowing the participant advance time to choose an option), the amber bubble turned green and an auditory signal (whistle) acted as the imperative signal to move. The participants had six trials in the practice session (two trials for each target distance in a randomised order) to familiarise themselves with the task. After each trial finished, participants returned to the red bubble to start another trial at their own pace.

In the baseline session, participants were asked to reach as fast as possible to the target under the same design as the practice trials. There were 27 trials in the baseline session with participants reaching nine times to each target distance (0.50, 0.65, 0.75 arm span). The target location was randomised. The feedback presented in text within the virtual display was either "Well done, that was fast" when the participant's movement time was faster than the previous trial for the same target distance, or "Too slow, try to be faster" when the movement time was slower than the previous trial for the same target distance. Following the baseline session, the median movement time (reach time) was calculated for each target distance from the kinematic data generated from the controller. This movement time was used as the target appearance time in the decision-making session (panel A in Figure 2.12).

The last session was the decision-making component, where the participant had to decide between two targets – a low reward option and a high reward option. As in the practice and baselines, the targets were represented as bubbles that participants were asked to reach towards in order to “pop”. The same trial initiation was used as in the previous sessions. The low reward option was always closer and at the same distance (0.35 arm span), and never disappeared. The high reward option was further (either 0.50, 0.65 or 0.75 arm span) and disappeared after a set time interval (this time interval was determined by the median time taken to hit the target during the baseline session calculated for each participant). If the high reward target was selected then the trial would time out if the target was not hit and a ‘miss’ was recorded. If the low reward target was selected then this target would remain until it was hit, meaning miss trials only occurred in response to high reward target selections. Target selection was determined by checking whether the hand was on the right or left of the midline at the high reward target’s elapse time (i.e. the median time taken from baseline session).

The targets could appear randomly either on the left or the right of the midline (high and low targets were randomly assigned to each side). The angular separation between the targets was 25 degrees (each target positioned 12.5 degrees from the midline). The start bubble was located on the midline at a height equivalent to 0.75 of the participant’s height and at a distance of 0.20 arm’s span. Participants reached 16 times for each bubble configuration in a quasi-random order (total of 48 trials). Participants were asked to keep their feet on the white spot on the virtual floor (panel B in Figure 2.12).

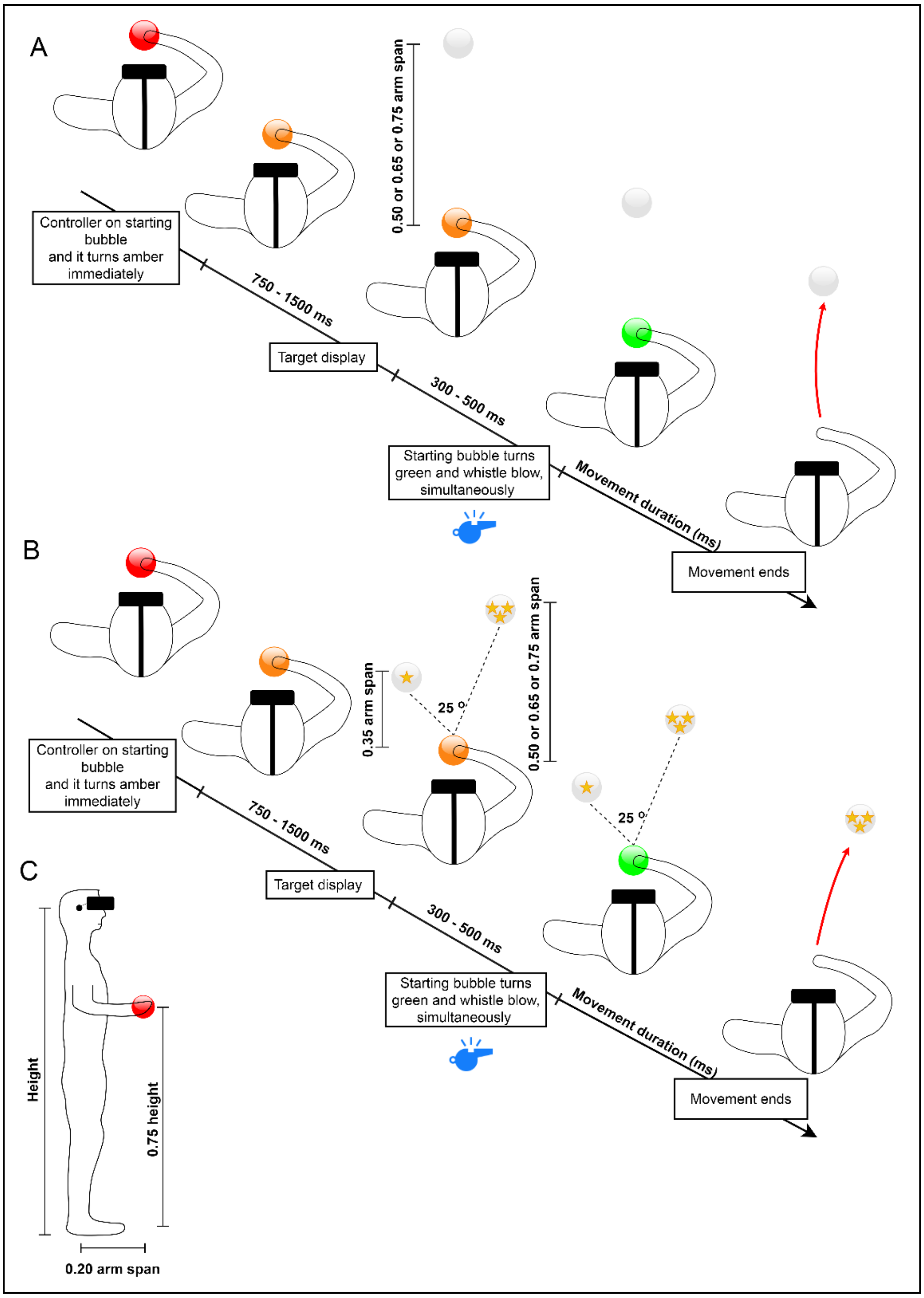

Figure 2.12 Panel A shows the participant from above in the practice and baseline sessions where one target appears at either 0.50 or 0.65 or 0.75 arm span at the midline. The lower line represents the sequence of the trial in milliseconds; from the participant landing on the start position (red target) to hearing the whistle (signal to move). Panel B shows participant from above in the decision-making session where the closer target (one star) appears at 0.35 arm span and the further target (three stars) appears at either 0.50 or 0.65 or 0.75 arm's span with an angular separation of 25°. The lower line represents the sequence of the trial; from the participant landing on the start position (red target) to hearing the whistle (signal to move). Panel C shows the participant standing on the dedicated spot wearing the VR headset; height is measured as the distance from the headset to the floor and the red target is presented in front of the participant at a distance of 0.20 arm span and 0.75 participant's height.

In principle, selecting the median movement time from the baseline session as the display time for the high reward targets should mean that the participants hit these targets on half of all trials in which they move to that target. This logic does not, however, account for the participants learning to move the controller more effectively within the virtual environment over the course of the experiment. In fact, pilot work suggested that the participants were able to hit the high reward target around 70% of the time when it was displayed for the median baseline movement time. This means that the high reward target had a greater expected value than the low reward target on every trial. This arrangement means that an entirely rational agent should select the high reward target on every trial once the expected value was learned, unless there were other costs associated with these targets. In the current experiment, it is reasonable to assume that the high reward targets had ‘motor costs’. These costs include the greater energy expenditure associated with reaching to further targets, but also the increased risk of falling when the centre of gravity is perturbed through extended arm reach.

2.7.3 General statistical analysis approach

Before conducting any inferential statistics, data were examined for violations of assumptions of normality through box- plots, Q–Q plots, histograms and Shapiro–Wilk test ($P < 0.05$), with transformations performed where necessary. A Z-score was calculated and ± 3 were assigned as a threshold to deal with outliers. To compare between experimental conditions, mixed model ANOVAs were computed, with target distance set as a repeated measures factor and Gender as a between-subjects factors with two levels. The primary analyses used frequency of selection as the dependent variable. Specific variations on this ANOVA are detailed within the methodology of individual experiments. Wherever sphericity was violated (examined via Mauchly's test), Greenhouse-Geisser corrections were applied and the adjusted p-values are reported (Bakeman, 2005). The statistical significance threshold was set at $p <.05$. Where significant main effects were observed, Bonferroni-corrected post-hoc p values are reported. Generalised eta squared (η_G^2) was calculated to indicate effect size. This effect size approach was adopted as it more readily allows comparisons between different research designs [(Olejnik & Algina, 2003); c.f. Partial eta squared]. Statistical analyses were performed using R version 3.3.1 running inside the R Studio Integrated Development Environment (RStudio, Boston, MA). Data wrangling was performed using the "Tidyverse" library (Wickham, 2017) and the "ezANOVA" package was used to compute ANOVAs. GGPlot2 was used to visualise the data (Wickham, 2016). The sample size in the thesis was similar to previous experiments carried out in the research lab (see; (Brookes et al., 2019; Flatters et al., 2014; Raw et al., 2019; Shire et al., 2016).

CHAPTER 3: EFFECT OF REWARD AND DISTANCE ON DECISION-MAKING (EXPERIMENT 1)

3.1 Introduction

Economical choices are an essential part of the decision-making processes but it is involved in small number of the decisions that human make in a daily bases. The sensorimotor system is involved in most of these daily decisions, to ensure the action execusion. However, researchers have barely draw attention to the influence of sensorimotor system in decision-making. As discussed earlier, Trommershauser et al., (2008) investigated combined the motor and cognitive aspect of decision-making. The experimental design presented here integrates the cognitive and sensorimotor decision-manking in the task execution. A simple daily action of reach to grasp, involves not only the reward expected from this action but also it encounter the sensorimotor cost associated with the action. This integration in decision-making has gain attention in recent years (Green et al., 2010; McDougle et al., 2016, 2019; Parvin et al., 2018).

In this chapter we are going to examine the effect of the reward on the decision-making behaviour. To do so three manipulations of the disappearing target were carried out. These manipulations were; two stars, three stars and the five stars for the disappearing target and one star for the fixed target.

Tha aim of this experiment was to examine the reward influence on the sensorimotor decision making. Two hypothesis were examined in this experiment; (i) reward would influence participants decision making in the virtual reality task and (ii) participants would reach more to the high reward target when the value is five stars compared to two stars and three stars.

3.2 Methods

3.2.1 Participants

One hundred and twenty adults (60 males; 57 right handed and 60 females; 57 right handed) from the University of Leeds participated in this study (mean age = 21 years, SD = 2.8). The participants were assigned randomly to one of three different groups: Two star (20 males and 20 females, mean age = 21.97 years, SD = 3.38) where the disappearing target worth two stars and the fixed target one star; Three star (20 males and 20 females, mean age = 20.45 years, SD = 2.73) where the disappearing target worth three stars and the fixed target one star; and Five star (20 males and 20 females, mean age = 20.80 years, SD = 1.83) where the disappearing target worth five stars and the fixed target one star. All participants gave their written informed consent, and the experiment complied with the ethical guidelines approved by the University of Leeds ethical committee (ethical approval number: 17-0181, date approved: 16/06/2017).

3.2.2 The task design

Participants undertook three sessions: a practice session, a baseline session, and a decision-making session as described in the general methods section. The participant's task in this experiment was to move a controller held in the preferred hand to hit the target. The controller position was tracked, and a virtual representation of the controller was visible throughout the experiment. Participants were assigned to one of three groups (two star; three star; and five star). The high reward target in the two star group had a value of two stars, in the three star group had a value of three stars, and in the five star group had a value of five stars. In all cases, the alternative option, the low reward target, was worth 1 star. The high reward targets were positioned at one of three distances from the starting position (0.50, 0.65 or 0.75 arm span). The low reward target was always positioned at 0.35 arm span (Panel A, B, and C in Figure 3.1). This produced a 2 (gender: female, male; between subjects) x 3 (groups: 2 star, 3 star, 5 star; between subjects) x 3 (target distance: near, medium, far; within-subjects) design.

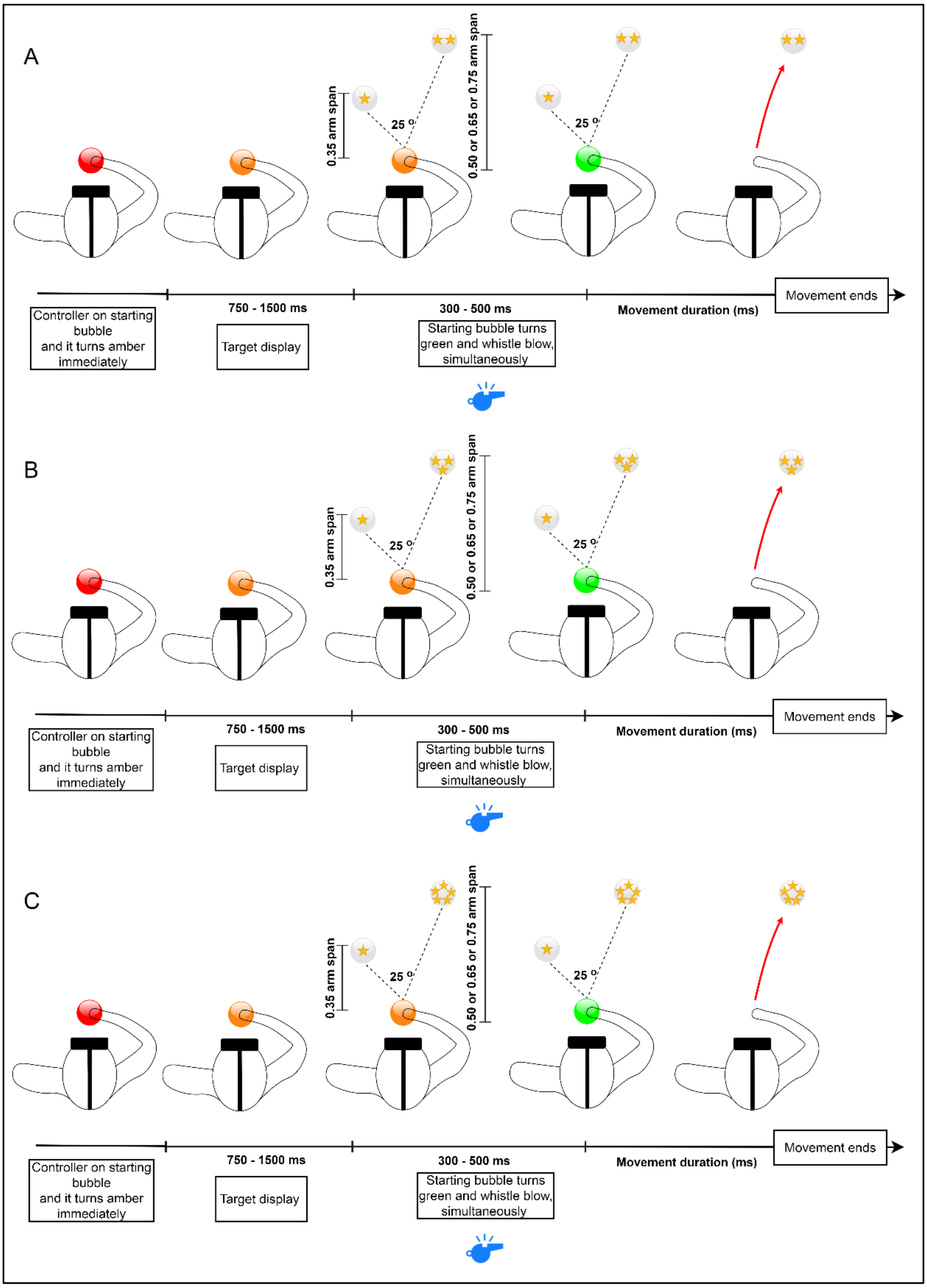

Figure 3.1 Panel A shows participant from above in the decision-making session where the closer target (one star) appears at 0.35 arm span and the further target (three stars) appears at either 0.50 or 0.65 or 0.75 arm's span with an angular separation of 25°. The lower line represents the sequence of the trial; from the participant landing on the start position (red target) to hearing the whistle (signal to move). Panel B and C show the same but for three stars and five stars manipulation.

3.3 Results

Before conducting any inferential statistics, data were examined for violations of assumptions of normality through box- plots, Q–Q plots, histograms and Shapiro–Wilk test ($P < 0.05$), with transformations performed where necessary. A Z-score was calculated and ± 3 were assigned as a threshold to deal with outliers. There were five possible trial outcomes in the experimental session: high reward target hit when the participants reached the high reward target on time, high reward target miss (when the participant selected but did not reach the high reward target on time), low reward target hit, premature (when they reached too early), and no-go (when participants did not move at all). Table 3.1 shows the percentage of each possible outcome.

Table 3.1 Percentage of trial outcomes with mean and standard deviation (SD).

Trial outcome	Mean (%)	SD (%)
High reward target hit	41.3	0.38
High reward target miss	12.1	0.70
Low reward target hit	38.5	0.39
Premature	5.7	1.03
No-go	2.4	1.57

Target distance had a significant main effect on the premature trials [$F(2, 228) = 15.99$, $p <.001$, $\eta_G^2 = 0.05$] and no-go trials [$F(2, 228) = 4.38$, $p =.013$, $\eta_G^2 = 0.02$]. There was a clear gradient whereby the most premature and no-go trials occurred when the high reward target was displayed near, and the least when it was displayed far. It is not clear why this pattern arose. The increased perceptual salience of the near target and a greater propensity for this high reward target to be selected might explain the premature trial pattern. The no-go pattern might have arisen because the values of expected utility are more similar when the high reward target is closer. There were no significant effects of gender or group on these no-go or premature trials (or any significant interactions F's < 2.01, p's > .13). We excluded the premature and no-go trials from further analysis of the data (i.e. 8.1% of trials in total were excluded).

3.3.1 Points obtained

The objective for participants was to collect as many points as possible. Thus, we first analysed the points obtained as a function of group, gender and target distance. A mixed model ANOVA showed no significant three way interaction between target distance, gender, and group [F(4, 228) = 0.69, p = .59, η_G^2 = 0.004] and no significant interaction between target distance and gender [F(2, 228) = 0.26, p = .76, η_G^2 = 0.0009]. There was a significant interaction between gender and group [F(2, 114) = 3.80, p = .02, η_G^2 = 0.03] and between group and target distance [F(4, 228) = 11.9, p < .001, η_G^2 = 0.07]. There was a significant main effect of target distance [F(2, 228) = 53.55, p < .001, η_G^2 = 0.16], gender [F(1, 114) = 8.53, p = .004, η_G^2 = 0.04], and group [F(2, 114) = 41.44, p < .001, η_G^2 = 0.3] (Figure 3.2).

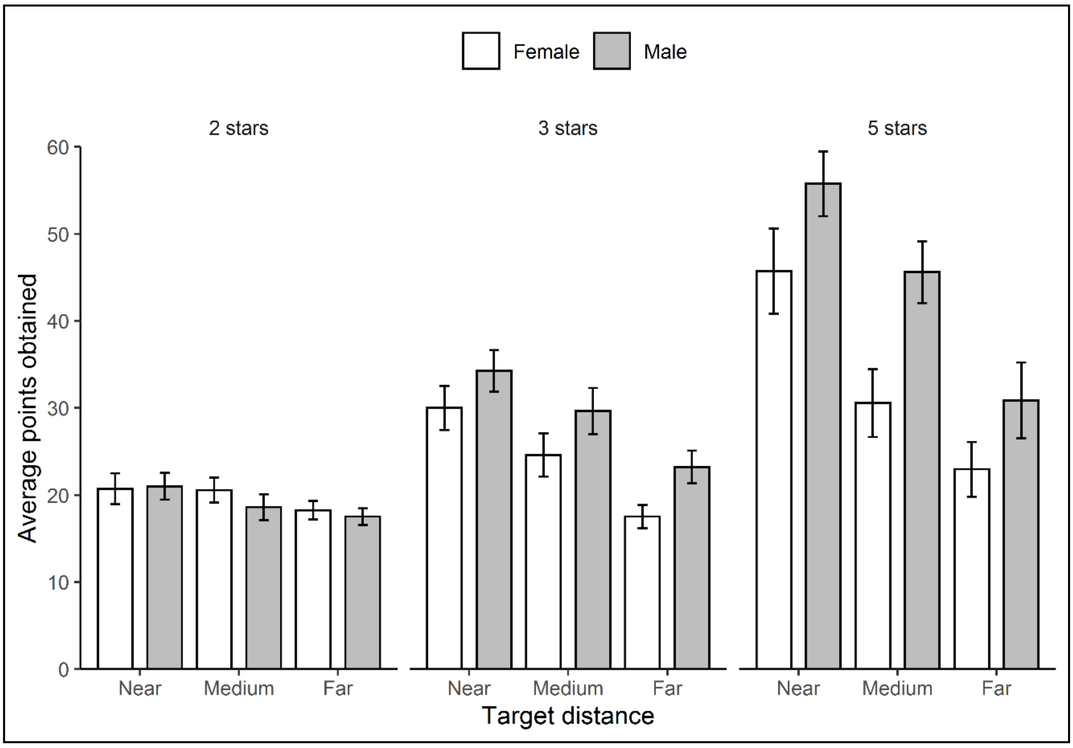

Figure 3.2 Average number of points obtained for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the three groups (left column = 2 stars, middle = 3 stars, right = 5 stars). Error bars show standard error of the mean.

As is evident from Figure 3.2 and the main effect of distance, fewer points were accrued as target distance increased, suggesting the participants were less likely to go for high reward target in these trials. In terms of the main effect of gender, males accrued more points than females (suggesting a greater propensity to go for high reward target). With regards to group; more points accrued when the high reward target had more points attached (a natural consequence if the participants were selecting the high reward target on some of the trials). The two-way interactions can be predicted from the three behavioural patterns above.

3.3.2 High reward target selection

We next looked at how often participants selected the high reward target. Figure 3.3 shows the percentage of high reward target selections (includes hits and misses) across all target distances and group for both genders. A mixed model

ANOVA on the high reward target selections showed no significant three way interaction between target distance, gender, and group [F(4, 228) = 0.46, p = .76, η_G^2 = 0.002]. There was no significant interaction between target distance and gender [F(2, 228) = 0.44, p = .63, η_G^2 = 0.001], nor between gender and group [F(2, 114) = 1.11, p = .33, η_G^2 = 0.01] or group and target distance [F(4, 228) = 0.25, p =.90, η_G^2 = 0.001]. There was a significant main effect of target distance [F(2, 228) = 160.86, p < .001, η_G^2 = 0.31] with participants being less likely to choose the high reward target as distance increased. There was also a significant main effect of gender [F(1, 114) = 7.06, p = .009, η_G^2 = 0.04] with males choosing the high reward target more frequently than females (supporting the theory behind the gender difference for points obtained). There was no main effect of group [F(2, 114) = 0.10, p = .90, η_G^2 = 0.001].

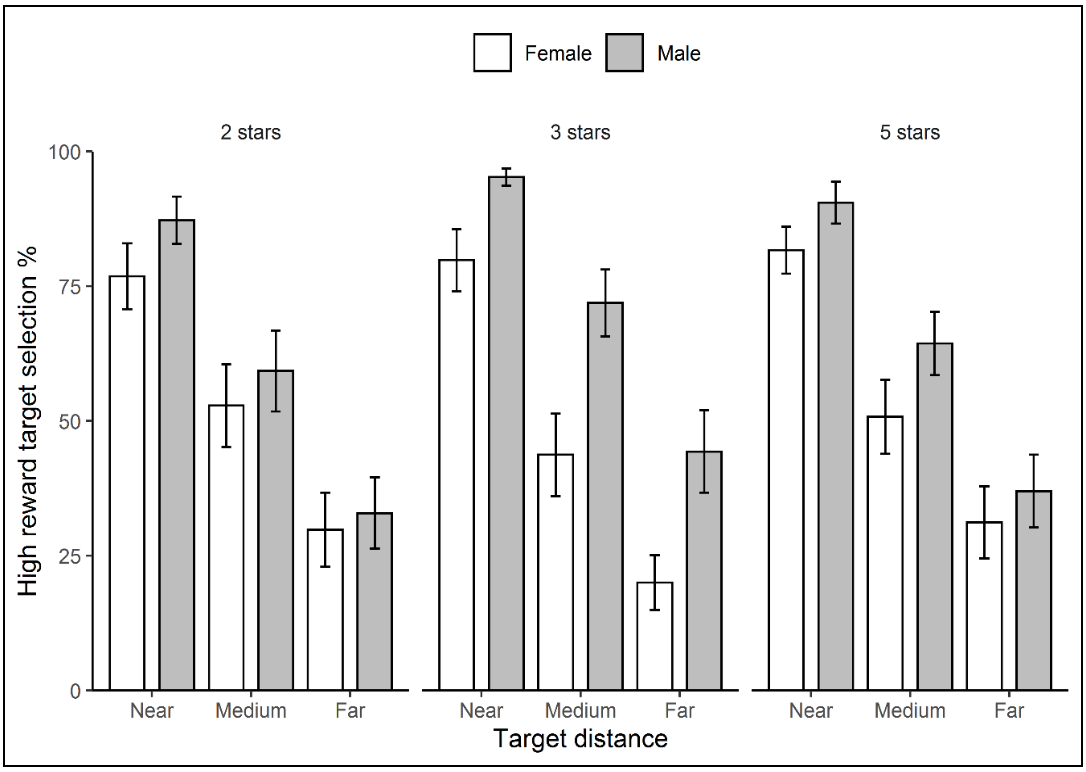

Figure 3.3 High reward target selection (percentage of trials in which the high reward target was selected; includes hits and misses) for females (unfilled bars) and males (filled bars) at each target distance (near, medium, far) across the three groups (left column = 2 stars, middle = 3 stars, right = 5 stars). Error bars show standard error of the mean.

3.3.3 High reward target hit

A mixed model ANOVA on the high reward target hits (as a percentage of high reward targets selected) across the group showed no significant three way interaction between target distance, gender, and group [F(4, 228) = 1.35, p = .25, η_G^2 = 0.01]. There was no significant interaction between target distance and gender [F(2, 228) = 0.44, p = .64, η_G^2 = 0.001], nor between gender and group [F(2, 114) = 2.31, p = .10, η_G^2 = 0.02] or group and target distance [F(4, 228) = 0.22, p =.92, η_G^2 = 0.001]. There was a significant main effect of target distance [F(2, 228) = 25.64, p < .001, η_G^2 = 0.09] reflecting the fact that the target was missed more frequently when it was further, and a significant main effect of gender [F(1, 114) = 9.37, p = .003, η_G^2 = 0.04] with males hitting the high reward target more frequently than females. There was no main effect of group [$F(2, 114) = 0.20$, $p = .81$, $\eta_G^2 = 0.001$] (Figure 3.4).

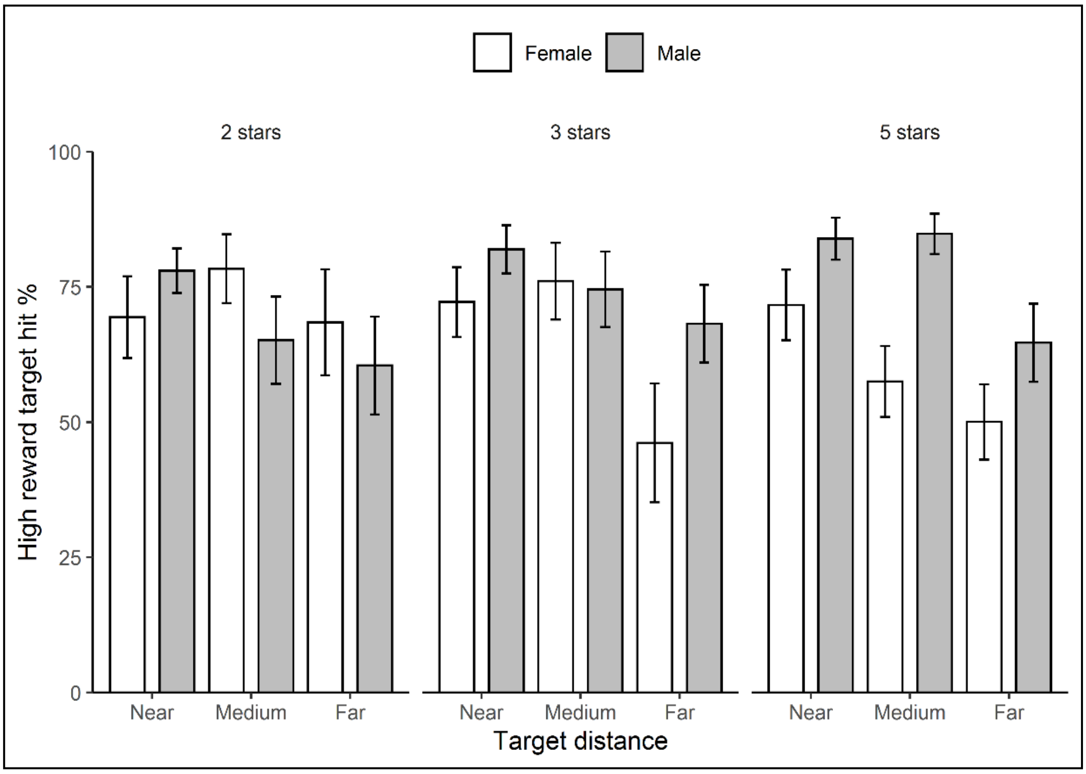

Figure 3.4 High reward target hits (percentage of selected targets) for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the three groups (left column = 2 stars, middle = 3 stars, right = 5 stars). Error bars show standard error of the mean.

The median time in which participants had to reach the high reward target was a function of the baseline trials, so there should not have been a target distance effect per se. The fact that one emerged presumably reflects the greater risks associated with moving further (in extreme falling over but, less dramatically, the potential need for on-line postural corrections).

3.4 Discussion

We designed a task in which participants needed to choose between two targets where one target was easier to hit (closer and on permanent display) versus a harder-to-hit target (further away and programmed to time-out). Our task forced participants to choose between two targets that differed in terms of their extrinsic value (number of stars) and their intrinsic (sensorimotor) cost. The data show that participants were influenced by the higher intrinsic costs of the further targets; when the high reward target was further away participants were less likely to select it. The data also show that males were more likely to select the high reward target than females. This is consistent with a plethora of studies employing classic cognitive decision-making tasks (e.g. gambling) where females show less risk taking behaviour compared to males (Bruce & Johnson, 1996; C. Harris et al., 2006; Powell & Ansic, 1997). These differences in risk aversion manifests in a number of away the confines of an experimental testing environment too: females rate risk more highly than males in a variety of scenarios including: driving, fire, crime, food safety and medical surgery (Breakwell, 2014).

Finally, it is noteworthy that the same selection frequencies were found across all groups (2, 3 and 5 star groups) despite the difference in the points available via the high reward target, suggesting that a sensorimotor cost threshold acts as an upper bound on the selection process. Participants could have ignored the intrinsic costs and just reached for the target that gave the highest extrinsic reward. The experimental arrangement would have meant the participants always reached for the high value target. The fact that this did not happen indicates that the participants were taking account of the intrinsic costs within the task. Alternatively, participants could have ignored the extrinsic value and have simply sought to minimise the intrinsic costs. This would have resulted in participants always selecting the low value target. The fact that this did not happen means that the participants were taking account of the extrinsic value of the targets and the sensorimotor costs within the task. Thus, the data indicate that participants are estimating value on the basis of both the extrinsic value of the targets and the intrinsic costs of the reaching movements.

Next, we sought to investigate whether the same pattern of results would emerge when motor noise was added to the paradigm. We hypothesised that the introduction of extrinsic motor noise in addition to the intrinsic and extrinsic costs present in Experiment 1 could push participants into a more risk-averse strategy. To this end, we asked participants to complete the task with their non-preferred hand, reasoning that use of the non-preferred hand would provide an elegant means of increasing sensorimotor noise.

We expected that by performing the task with the non-preferred hand, performance would be compromised. This assumption was predicated in previous research which has consistently show slower performance with the non-preferred hand relative to the preferred hand (Cramond et al., 1989; Fromm-Auch & Yeudall, 1983). Movements with the non-preferred hand are also less accurate and more variable (Carey & Liddle, 2013; Carson, 1993; Elliott et al., 1993; Schaffer & Sainburg, 2017). There is also a body of work demonstrating interference when tasks which have an additional component to them are employed (Baddeley & Della Sala, 1996; Theill et al., 2011; Yogev et al., 2005)- this effect is most pronounced when participants are asked to execute actions with their non-preferred hand (Strenge & Niedekberger, 2008; Yamashita, 2010). Consistent with this, neuroimaging research has also shown increased cortical activity when simple motor tasks are completed with the non-preferred hand relative to the preferred (Mattay et al., 1998). Crucially however for this manipulation, the impairments in handedness seem to be exclusive to the control component of action and not the prediction element (Mathew et al., 2019). Recent research coupling eye tracking with a hand tracking task showed the expected asymmetry in handedness for accuracy, but eye tracking, providing an index of the participants ability to predict the visual consequences of their hand movements, did not vary according to hand condition. Here, to ensure that the task was comparable to the first experiment in all elements with the exception of motor control, task difficulty was manipulated in the same way (calculated the baseline median movement times).

CHAPTER 4: EFFECT OF MOTOR NOISE ON DECISION-MAKING (EXPERIMENT 2)

4.1 Introduction

Hand control is contralateral; the left hemisphere of the brain controls the right hand and the right hemisphere of the brain controls the left hand (Annett, 1981). Handedness is divided into measures of preference and performance. Hand preference is defined as the preferred hand to complete a specific task while hand performance is to differentiate between right and left hand on task execution (McManus & Bryden, 1992). It has been reported that performance increased when using the preferred hand opposed to the non-preferred hand. Annett (1981) examined the manual speed and hand preference and found that subject moves to the objects faster when used their preferred hand compared to the non-preferred hand. The task was moving pegs from one end of a table to another end while recrding the movement time. Moreover, other researchers have suggested that more effort is required when the non-preferred hand is used in task execution (Jäncke et al., 1998).

Motor control and performance is more efficient when using the preferred hand compared to the non-preferred hand. Using non preferred hand is supposed to reduce the motor performance level. Some studies have reported that both right and left handed subjects showed similar motor performance level when the preferred hand is used. However, when using the non-preferred hand, left-handed subjects performed better compared to their right-handed peers when the non-preferred hand is used (Hoffmann, 1997). Several studies have found that the time to complete manual dexterity tests is less for the preferred compared to the non-preferred hand (Bryden & Roy, 2005; Wang et al., 2011). Moreover, the reaching movement accuracy and variability is better when using the preferred hand compared to the non-preferred hand (Carey & Liddle, 2013; Elliott et al., 1993; Schaffer & Sainburg, 2017).

The concept of motor equivalence is one of the main concepts in motor control. The idea that one can achieve same goal or task using different limb or muscles (Bernstein, 1967; Head et al., 1920). On aiming movement studies, Zuoza et al., (2009) examined right handed male participants and found that the preferred hand was more accurate than the non-preferred hand. Moreover the preferred hand showed less average and peak velocity in task execution.

In this experiment we examined the effect of handedness on the decision-making in our task. The aim of this experiment was to examine the effect of motor noise (using the non-preferred hand) on the decision making. We hypothesised that participants would reach to the high reward target less frequently in the motor noise group compared to the control group.

4.2 Methods

4.2.1 Participants

Eighty adults (40 males; 37 right handed and 40 females; 35 right handed) from the University of Leeds were included in this study (mean age = 20.8 years, SD = 2.6). Forty participants were recruited to from a 'motor noise' group. The group were recruited in the same manner as the participants in the first experiment so allocation to the group was random. The 'motor noise' group used their non-preferred hand to complete the task (20 males and 20 females, mean age = 21.2 years, SD = 2.4). We used the three star group from the first experiment (20 males and 20 females, mean age = 20.4 years, SD = 2.7) to act as a control group. All participants gave their written informed consent, and the experiment complied with the ethical guidelines approved by the University of Leeds ethical committee (ethical approval number: 17-0181, date approved: 16/06/2017).

4.2.2 The task design

Participants undertook three sessions: a practice session, a baseline session, and a decision-making session as described in the general methods section. The participant's task in the motor noise group was to move a controller held in the non-preferred hand to hit the target. The control group had performed the same task but with their preferred hand. The controller position was tracked and a virtual representation of the controller was visible throughout the experiment. The experiment configuration for both groups (motor noise and control group) was low reward target (one star) vs high reward target (three star). As in Experiment 1, the high reward targets were positioned at one of three distances from the starting position (0.50, 0.65 or 0.75 arm span). The low reward target was always positioned at 0.35 arm span (Figure 4.1). This produced a 2 (gender: female, male; between subjects) x 2 (group: control, motor noise; between subjects) x 3 (target distance: near, medium, far; within subjects) design.

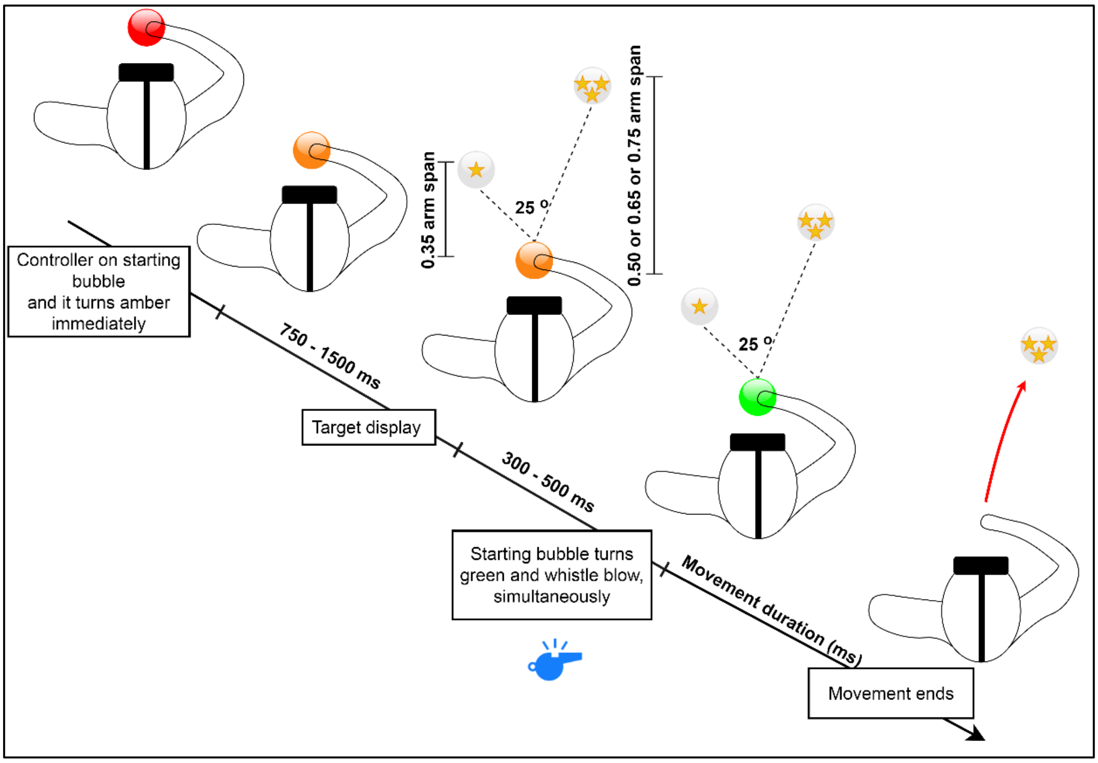

Figure 4.1 Participant from above in the decision-making session where the closer target (one star) appears at 0.35 arm span and the further target (three stars) appears at either 0.50 or 0.65 or 0.75 arm's span with an angular separation of 25°. The lower line represents the sequence of the trial; from the participant landing on the start position (red target) to hearing the whistle (signal to move).

4.3 Results

Before conducting any inferential statistics, data were examined for violations of assumptions of normality through box- plots, Q–Q plots, histograms and Shapiro–Wilk test ($P < 0.05$), with transformations performed where necessary. A Z-score was calculated and ± 3 were assigned as a threshold to deal with outliers. There were five possible trial outcomes in the experimental session: high reward target hit when the participants reached the high reward target on time, high reward target miss (when the participant selected but did not reach the high reward target on time), low reward target hit, premature (when they reached too early), and no-go (when participants did not move at all). Table 4.1 shows the percentage of each possible outcome.

Table 4.1 Percentage of trial outcomes with mean and standard deviation (SD).

Trial outcome	Mean (%)	SD (%)
High reward target hit	42.7	0.47
High reward target miss	11.9	0. 89
Low reward target hit	38.1	0. 49
Premature	5.7	1.2
No-go	1.5	2.5

There was a significant main effect of target distance [F(2, 152) = 5.88, p = .003, η_G^2 = 0.02] in the premature trials but not in the no-go trials [F(2, 152) = 1.74, p = .17, η_G^2 = 0.01]. There was no effect of gender in the premature trial [F(1, 76) = 0.04, p = .84] nor the no-go trials [F(1, 76) = 0.01, p = .90, η_G^2 = 0.0001]. We excluded the premature and no-go trials from further analysis of the data (i.e. 7.2% of trials in total were excluded).

4.3.1 Points obtained

A mixed model ANOVA on the on points obtained showed that there was not a significant three way interaction between target distance, gender, and group [F(2, 152) = 0.46, p = .62, η_G^2 = 0.002]. There was no significant interaction between target distance and gender [F(2, 152) = 0.38, p = .68, η_G^2 = 0.002], nor between target distance and group [F(2, 152) = 0.05, p = .94, η_G^2 = 0.0003], or between group and gender [F(1, 76) = 1.64, p = .20, η_G^2 = 0.01]. There was a significant main effect of target distance [F(2, 152) = 46.34, p < .001, η_G^2 = 0.19] with more points being obtained when the high reward target was closer, but no main effect of gender [F(1, 76) = 3.04, p = .08, η_G^2 = 0.02] nor of group [F(1, 76) = 0.01, p = .91, η_G^2 = 0.0001] (Figure 4.2).

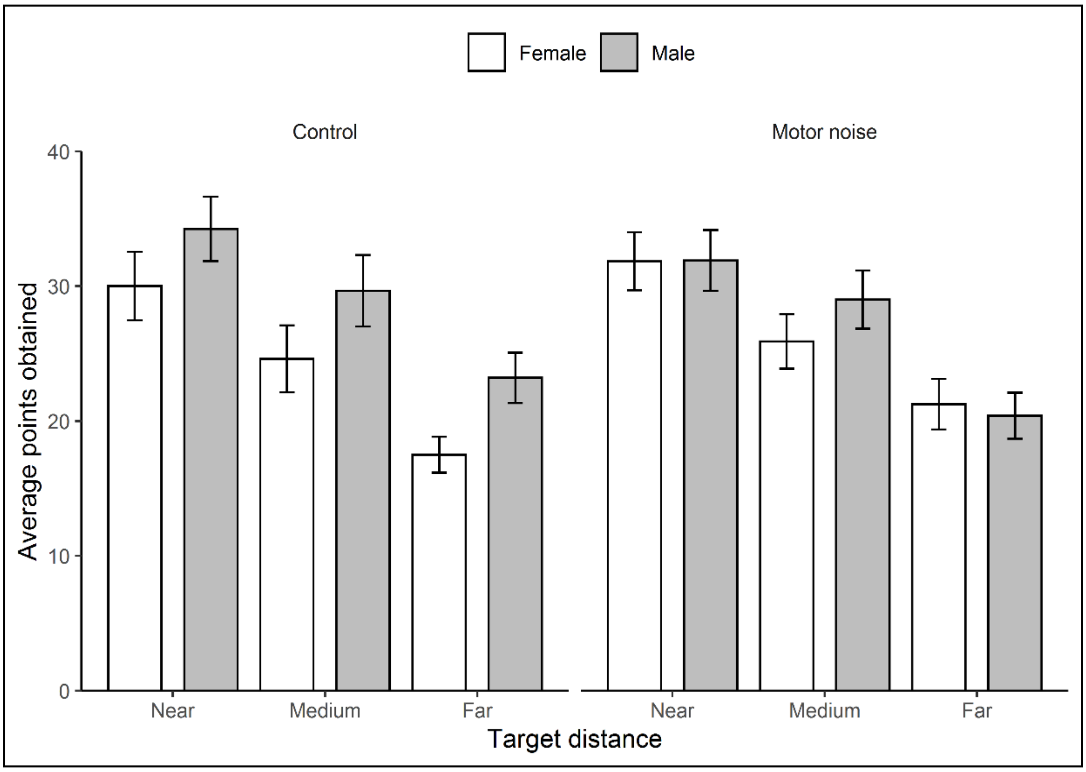

Figure 4.2 Average number of points obtained for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the two groups (left column = control group, right column = motor noise group). Error bars show standard error of the mean.

4.3.2 High reward target selection

A mixed model ANOVA on the high reward target selection showed that there was no significant three way interaction between target distance, gender, and group [F(2, 152) = 1.83, p = .16, η_G^2 = 0.007]. There was no significant interaction between target distance and gender [F(2, 152) = 0.71, p = .49, η_G^2 = 0.003], nor between target distance and group [F(2, 152) = 0.002, p = .99, η_G^2 = 0.0001]. However the interaction between group and gender was significant [F(1, 76) = 3.77, p = .05, η_G^2 =

0.03] with gender differences appearing more apparent in the control group compared to the motor noise group. There was a significant main effect of target distance [F(2, 152) = 170.43, p < .001, η_G^2 = 0.42] with participants being less likely to choose the high reward target as distance increased, and main effect of gender [F(1, 76) = 6.8. p = .01, η_G^2 = 0.05] with males selecting the high reward target more often than females, but no main effect of group [F(1, 76) = 0.004, p = .94, η_G^2 = 0.0001] (Figure 4.3).

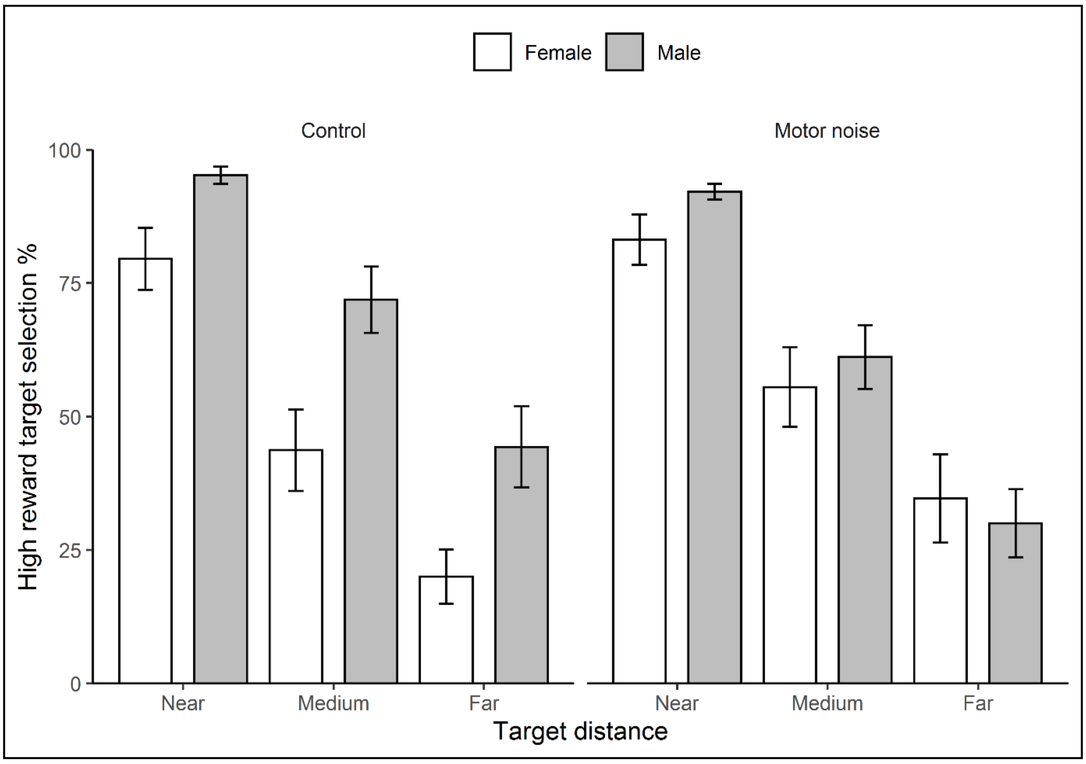

Figure 4.3 High reward target selection (percentage of trials in which the high reward target was selected; includes hits and misses) for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the two groups (left column = control group, right column = motor noise group). Error bars show standard error of the mean.

4.3.3 High reward target hit

A mixed model ANOVA on the high reward target hits across the group showed that there was no significant three way interaction between target distance, gender, and group [F(2, 152) = 1.59, p = .20, η_G^2 = 0.009]. There was no significant interaction between target distance and gender [F(2, 152) = 0.47, p = .62, η_G^2 = 0.002], nor between target distance and group [F(2, 152) = .17, p = .84, η_G^2 = 0.001] or between group and gender [F(1, 76) = 3.17, p = .07, η_G^2 = 0.02]. There was a significant main effect of target distance [F(2, 152) = 15.52, p < .001, η_G^2 = 0.08] with participants being less likely to hit the high reward target as distance increased, but no main effect of gender [F(1, 76) = 2.6, p = .10, η_G^2 = 0.01] nor main effect of group [F(1, 76) = 0.17, p = .67, η_G^2 = 0.001] (Figure 4.4).

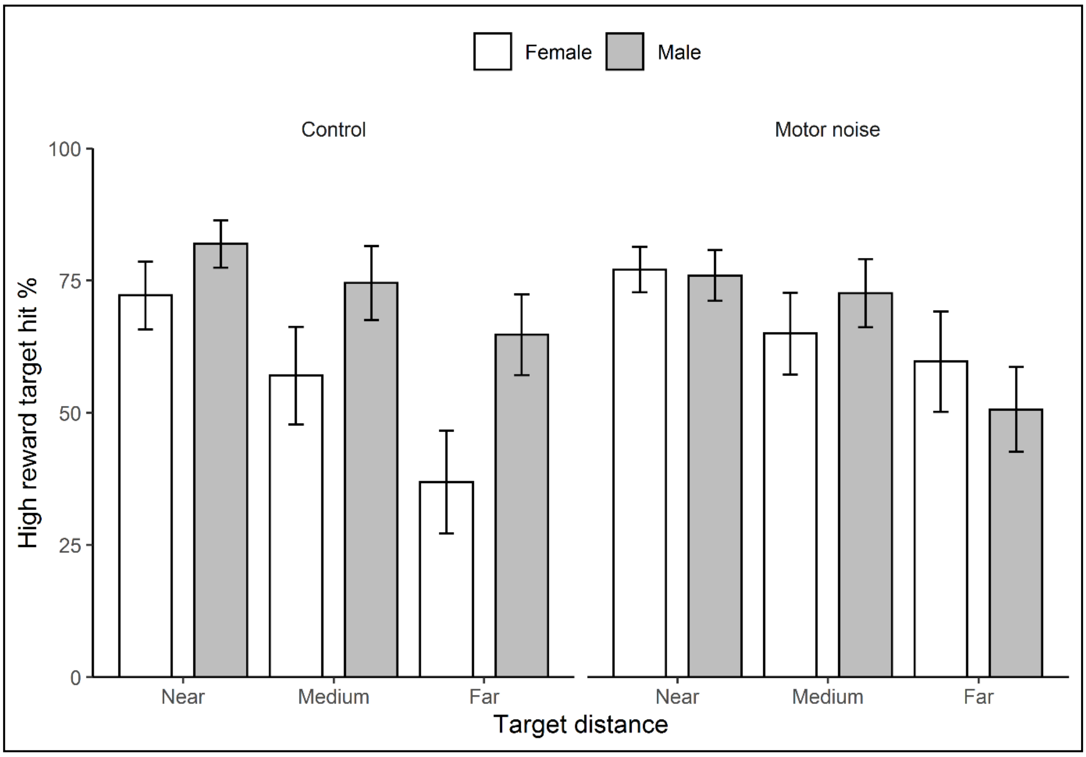

Figure 4.4 High reward target hits (percentage of selected targets) for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the two groups (left column = control group, right column = motor noise group). Error bars show standard error of the mean.

4.4 Discussion

The task from the previous experiment was repeated, but this time manipulating motor noise (whilst keeping the expected gain constant) by asking one group of participants to complete the task using their non-preferred hand. Using the preferred hand improves the motor performance level compared to the non-preferred hand. Hoffman et al., (1997) have reported that handedness did not affect the motor performance, but left handed participants performed better when using the non-preferred hand than the right handed participants. We found the same selection frequencies as in Experiment 1, with males selecting the high reward target more often than females (although this was mediated by group and more evident in the control group than the motor noise one), and participants being less likely to select the high reward target as the distance of that target increased. The motor noise manipulation had no effect, suggesting that participants were well-tuned to the sensorimotor costs associated. This result was not possible to predict a priori. The participants all reported a strong hand preference and thus would have been fully aware of their reduced abilities with their non-preferred hand. Some studies have shown that reaching movement accuracy is better in preferred hand compared to the non-preferred hand (Carey & Liddle, 2013; Schaffer & Sainburg, 2017). It is reasonable to expect that this knowledge might have been sufficient to alter the decision over whether to select the safe or risky target. The fact that this group of participants made the same selection choices as the control group indicates that human adults are well tuned to the task relevant sensorimotor capacity.

CHAPTER 5: EFFECT OF SENSORY NOISE ON DECISION-MAKING (EXPERIMENT 3)

5.1 Introduction

We next decided to examine the effects of sensory noise. As with motor noise, we hypothesised that the introduction of extrinsic sensory noise in addition to the intrinsic and extrinsic cost presented in Experiment 1 might drive participants into more risk-averse behaviour. Thus, we asked participants to complete the task without online visual feedback of the controller, as the absence of online visual feedback should induce sensory noise.

The removal of visual feedback regarding the hand position should hinder the action selection and execution processes. It delays the error correction in action execution as shown in previous studies (for review see Elliott, Digby; Helsen, Werner; Chua, 2001). This idea stems from the notion that the online correction in reaching movement comes from the visual information gathered during action execution (Saunders, 2004). The absence of visual feedback of the hand has been found to produce: (i) end-point variability in reaching (Hay & Beaubaton, 1986; Keele & Posner, 1968); (ii) a tendency to underestimate the target distance (Prablanc & Péisson, 1990); (iii) an increase in reaching path curvature (Goodbody & Wolpert, 1999); (iv) decreased error correction (Khan & Franks, 2000) and (v) increased reaction times (Bennett & Davids, 1996).

The aim of this experiment was to examine the effect of sensory noise (no online visual representation of the controller) on the decision making. We hypothesised that participants would reach to the high reward target less frequently in the sensory noise group compared to the control group.

5.2 Methods

5.2.1 Participants

Eighty adults (40 males; 38 right handed and 40 females; 36 right handed) from the University of Leeds participated in this study (mean age = 21.8 years, SD = 3.6). The participants were assigned randomly to one of two different groups: a sensory noise group (20 males and 20 females, mean age = 23.1 years, SD = 3.8); and a control group (20 males and 20 females, mean age = 20.4 years, SD = 2.7). The control group is presented from the first experiment (the three star group). All participants gave their written informed consent, and the experiment complied with the ethical guidelines approved by the University of Leeds ethical committee (ethical approval number: 17-0181, date approved: 16/06/2017).

5.2.2 The task design

Participants undertook three sessions: a practice session, a baseline session, and decision-making session as described in the general methods section. The participant's task in this experiment was to move a controller held in the preferred hand to hit the target. For the sensory noise group, the controller position was tracked and a virtual representation of it was visible in the practice session only. For the remaining sessions the controller disappeared after the whistle. When the participant hit the target, the controller would appear again to help them navigate to the starting position (a red bubble). A virtual representation of the controller was visible throughout the experiment for the control group. The experiment configuration for both groups (sensory noise and control group) was low reward target (one star) vs high reward target (three star). As in Experiment 1, the high reward targets were positioned at one of three distances from the starting position (0.50, 0.65 or 0.75 arm span). The low reward target was always positioned at 0.35 arm span (Figure 5.1). This produced a 2 (gender: female, male; between subjects) x 2 (group: control, sensory noise; between subjects) x 3 (target distance: near, medium, far; within subjects) design.

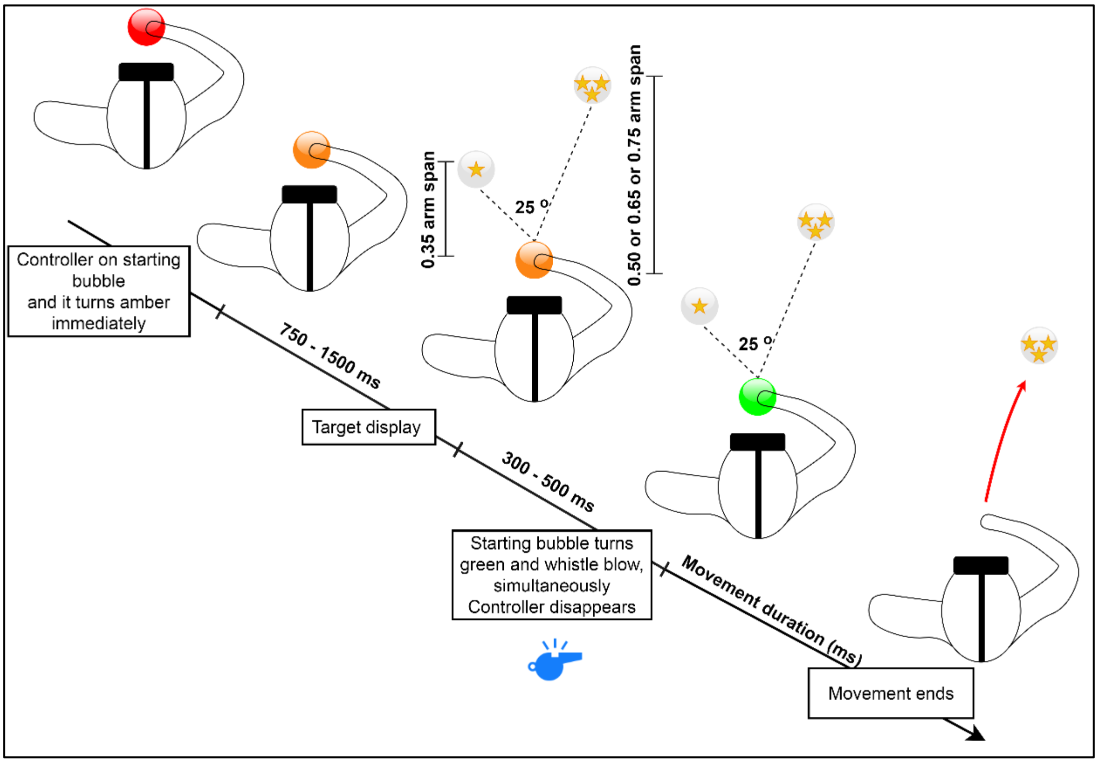

Figure 5.1 Participant from above in the decision-making session where the closer target (one star) appears at 0.35 arm span and the further target (three stars) appears at either 0.50 or 0.65 or 0.75 arm's span with an angular separation of 25°. The lower line represents the sequence of the trial; from the participant landing on the start position (red target) to hearing the whistle (signal to move). The controller disappears at the whistle (signal to move).

5.3 Results

Before conducting any inferential statistics, data were examined for violations of assumptions of normality through box- plots, Q–Q plots, histograms and Shapiro–Wilk test ($P < 0.05$), with transformations performed where necessary. A Z-score was calculated and ± 3 were assigned as a threshold to deal with outliers. There were five possible trial outcomes in the experimental session: high reward target hit when the participants reached the high reward target on time, high reward target miss (when the participant selected but did not reach the high reward target on time), low reward target hit, premature (when they reached too early), and no-go (when participants did not move at all). Table 5.1 shows the percentage of each possible outcome.

Table 5.1 Percentage of trial outcomes with mean and standard deviation (SD).

Trial outcome	Mean (%)	SD (%)
High reward target hit	41.1	0.46
High reward target miss	13.4	0.81
Low reward target hit	38.6	0.48
Premature	5.1	1.32
No-go	1.6	2.36

There was a significant main effect of target distance [$F(2, 152) = 6.39$, $p = .002$, $\eta_G^2 = 0.03$] with the premature trials but not with the no-go trials [$F(2, 152) = 1.71$, $p = .18$, $\eta_G^2 = 0.01$]. There was no effect of gender in the premature trials [$F(1, 76) = 0.27$, $p = .6$, $\eta_G^2 = 0.002$] nor the no-go trials [$F(1, 76) = 0.43$, $p = .51$, $\eta_G^2 = 0.001$]. We excluded the premature and no-go trials from further analysis of the data (i.e. 6.7% of trials in total were excluded).

5.3.1 Points obtained

A mixed model ANOVA on the on points obtained showed that there was no significant three way interaction between target distance, gender, and group [F(2, 152) = 0.23, p = .79, η_G^2 = 0.001]. There was no significant interaction between target distance and gender [F(2, 152) = 0.09, p = .91, η_G^2 = 0.0005], nor between target distance and group [F(2, 152) = 0.93, p = .39, η_G^2 = 0.005], or between group and gender [F(1, 76) = 2.08, p = .15, η_G^2 = 0.01]. There was a significant main effect of target distance [F(2, 152) = 51.5, p < .001, η_G^2 = 0.22] with more points being obtained when the high reward target was closer, but no main effect of gender [F(1, 76) = 2.29, p = .13, η_G^2 = 0.01] nor of group [F(1, 76) = .56, p = .45, η_G^2 = 0.004] (Figure 5.2).

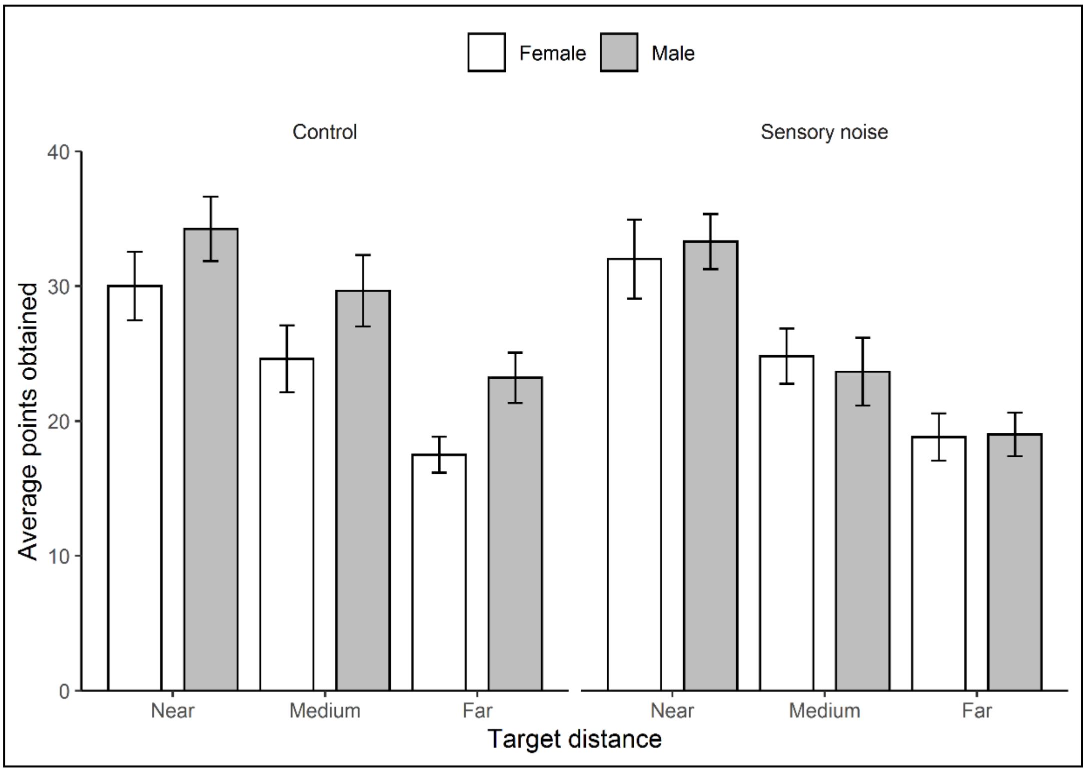

Figure 5.2 Average number of points obtained for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the two groups (left column = control group, right column = sensory noise group). Error bars show standard error of the mean.

5.3.2 High reward target selection

A mixed model ANOVA on the high reward target selection showed that there was not a significant three way interaction between target distance, gender, and group [F(2, 152) = 0.70, p = .49, η_G^2 = 0.003]. There was no significant interaction between target distance and gender [F(2, 152) = 0.55, p = .57, η_G^2 = 0.002], nor between target distance and group [F(2, 152) = 0.93, p = .39, η_G^2 = 0.004]. However, there was a significant interaction between group and gender [F(1, 76) = 4.61, p = .03, η_G^2 = 0.03] with group differences appearing more apparent in the control group compared to the sensory noise group. There was a significant main effect of target distance [F(2, 152) = 200.25, p < .001, η_G^2 = 0.47] with participants being less likely to choose the high reward target as target distance increased, and main effect of gender [F(1, 76) = 7.25, p = .008, η_G^2 = 0.05], with males being more likely to select the high reward target than females, but not main effect of group [F(1, 76) = 0.02, p = .87, η_G^2 = 0.0002] (Figure 5.3).

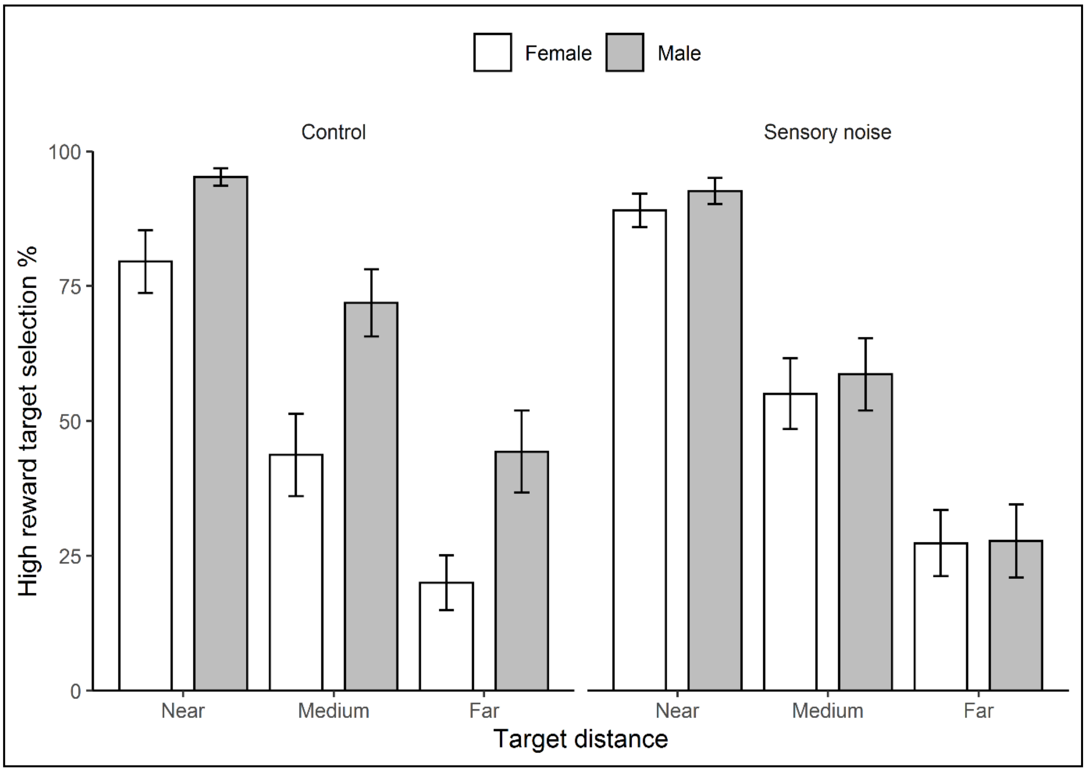

Figure 5.3 High reward target selection (percentage of trials in which the high reward target was selected; includes hits and misses) for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the two groups (left column = control group, right column = sensory noise group). Error bars show standard error of the mean.

5.3.3 High reward target hit

A mixed model ANOVA on the high reward target hits across the group showed that there was no significant three way interaction between target distance, gender, and group [F(2, 152) = 0.92, p = .39, η_G^2 = 0.006]. There was also no significant interaction between target distance and gender [F(2, 152) = 0.22, p = .79, η_G^2 = 0.001], nor between target distance and group [F(2, 152) = 0.70, p = .49, η_G^2 = 0.004] or between group and gender [F(1, 76) = 2.45, p = .12, η_G^2 = 0.01]. There was a significant main effect of target distance [F(2, 152) = 24.14, p < .001, η_G^2 = 0.13] with participants being less likely to hit the high reward target as target distance increased, and main effect of gender [F(1, 76) = 3.87, p = .05, η_G^2 = 0.02], with females less likely to hit the target than males, but no main effect of group [F(1, 76) = 1.41, p = .23, η_G^2 = 0.009] (Figure 5.4).

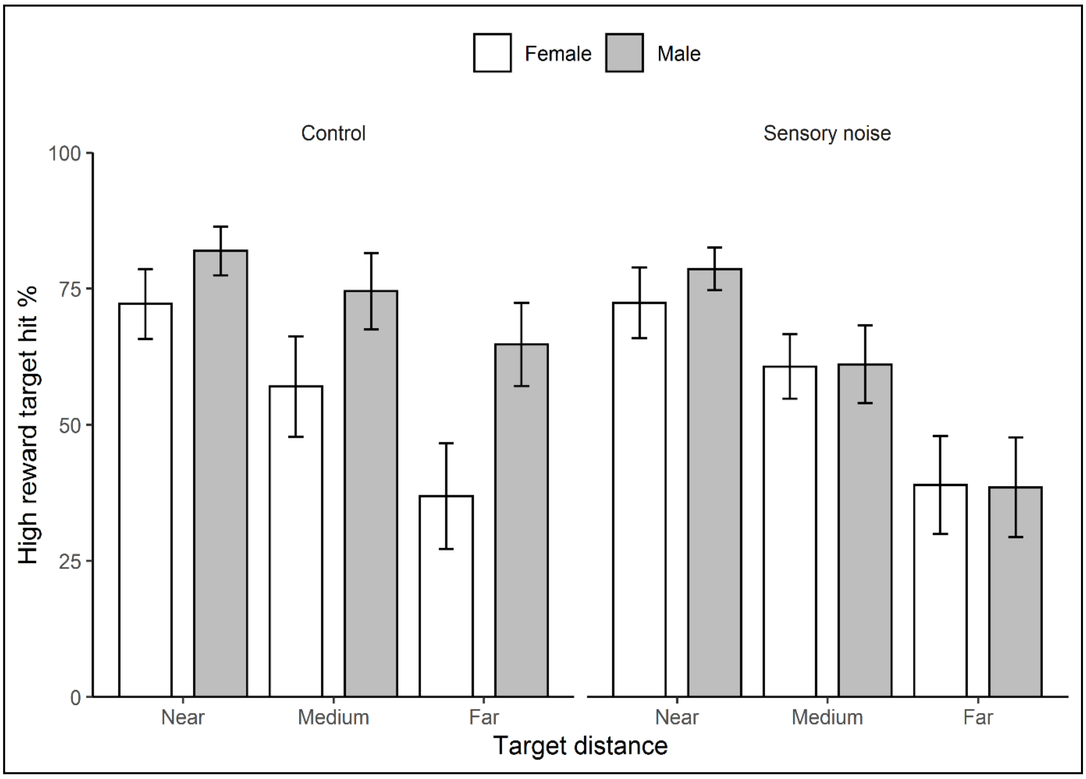

Figure 5.4 High reward target hits (percentage of selected targets) for females (unfilled bars) and males (filled bars) at each target distance (near, medium and far) across the two groups (left column = control group, right column = sensory noise group). Error bars show standard error of the mean.

5.4 Selection biases across experiments 1 – 3

5.4.1 Lateral or ipsilateral selection

We assumed that if there was no laterality bias, the participant would reach to the ipsilateral side 50% of the time (the same side as their preferred hand) because the targets were randomly distributed on the two sides. For 200 participants (between subject and noise group), the ipsilateral side was selected 51% of the time. A one sample t-test shows that this was not statistically significant from 50% [t(199) = 1.85, p = .06]. We also examined right vs left selection, and a paired sample t-test showed no significant difference between the right and left side selected [t(199) = -0.89, p = .37].

5.4.2 Selection bias based on previous trial – laterality

We calculated the probability of participants selecting a target direction (right or left) based on the previous direction selected (i.e. the probability that the left target would be selected on a trial following selection of the left target). Repeated measure ANOVA revealed no significant interaction between selected side and target distance [F(2, 594) = 0.70, p = .49, η_G^2 = 0.002]. There was no main effect of selected side [F(1, 594) = 0.10, p = .74, η_G^2 = 0.001] or target distance [F(2, 594) = 0.85, p = .42, η_G^2 = 0.003]. Thus, the previous side selected did not affect the subsequent target selection. These results show that participants were not showing a laterality bias and choosing one side more than the other.

5.4.3 Selection bias based on previous trial – reward magnitude

The probability of participants selecting a safe or risky target according to the previous trial behaviour was calculated (i.e. if they chose the risky target how likely were they to select the safe target on the subsequent trial). A repeated measures ANOVA showed a significant interaction between previous selection (risky vs safe) and target distance [F(2, 593) = 3.7, p = .02, η_G^2 = 0.01]. There was no main effect of previous selection [F(1, 593) = 0.82, p = .36, η_G^2 = 0.001], but there was a main effect of target distance [F(2, 593) = 127.9, p < .001, η_G^2 = 0.30]. If the previous trial was safe then the participant was more likely to subsequently select a risky trial than they were if the previous trial was risky, but this effect interacted with target distance such that it was negligible at near, moderate at the middle target distance, and largest for further targets (Figure 5.5). These results suggest there was a tendency towards exploration across the participants.

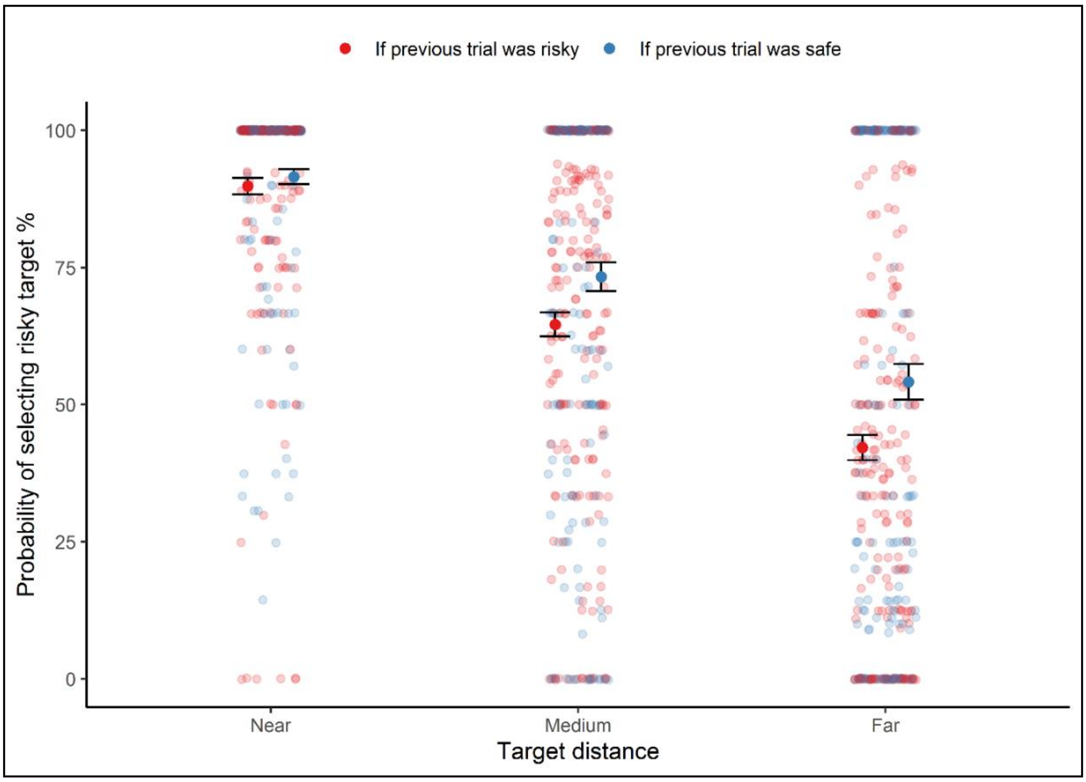

Figure 5.5 Probability of selection (risky or safe) compared to the previous trial as a function of target distance. Mean and standard error with dots as a single participant's observation. Red dots are showing the observations when the previous trial selection was risky, and blue dots are showing the observations when the previous trial selection was safe.

5.4.4 Selection bias based on previous trial – success rate

We analysed the participant's selection (risky or safe) according to whether the previous trial outcome was successful. Repeated measure ANOVA showed a significant interaction between outcome and target distance [$F(2, 597) = 3.1$, $p = .04$, $\eta_G^2 = 0.01$]. There was a significant main effect of outcome [$F(1, 597) = 216.6$, $p < .001$, $\eta_G^2 = 0.26$], and of target distance [$F(2, 597) = 89.5$, $p < .001$, $\eta_G^2 = 0.23$]. Figure 5.6 shows that participants were more likely to select the risky target if the previous target was successfully hit than if it was missed – and this effect was greatest for the middle distance targets. These results suggest there was a tendency towards exploitation across the participants.

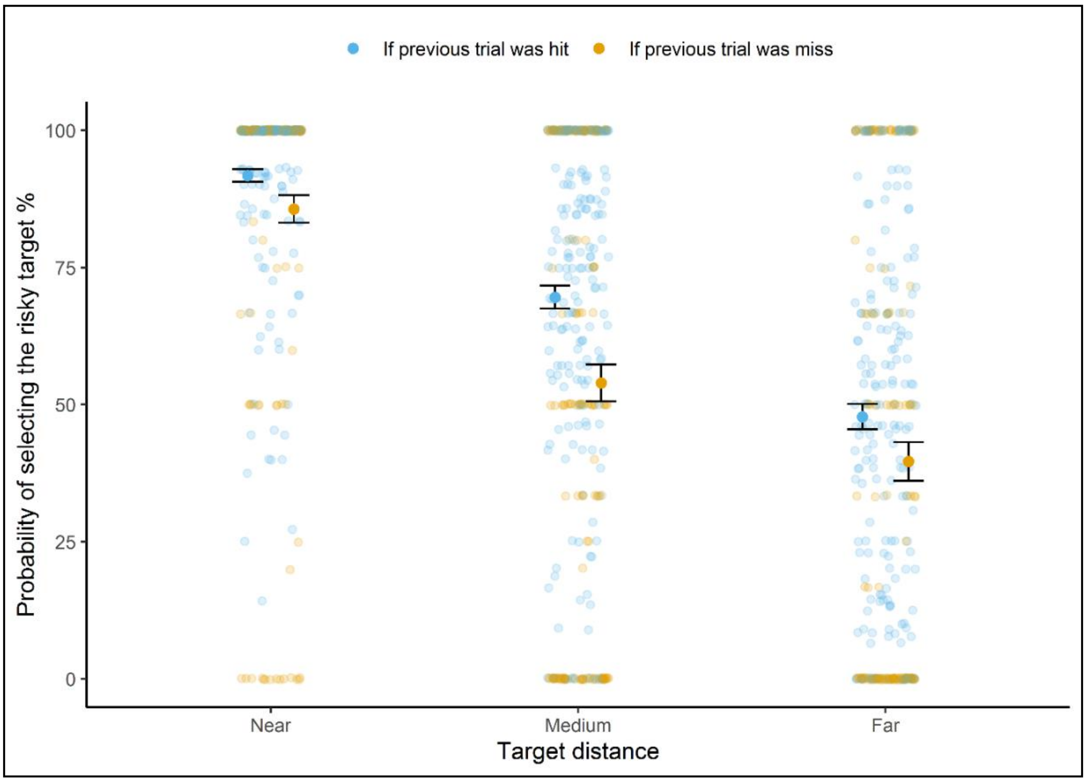

Figure 5.6 Probability of selecting the risky target compared to the previous trial outcome as a function of target distance. Mean and standard error with dots as a single participant's observation. Blue dots are showing the observations when the previous trial outcome was hit, and yellow dots are showing the observations when the previous trial outcome was miss.

5.4.5 Selection bias based in previous trial: success rate, target distance and reward magnitude

In order to explore further the effect of outcome and previous choice on current trial selection*,* a repeated measure ANOVA was conducted. The ANOVA had three factors: previous outcome (hit vs miss), target distance (near, medium, far) and previous trial selection type (risky vs safe). The ANOVA showed a significant three way interaction [$F(2, 1102) = 16.07$, $p < .001$, $\eta_G^2 = 0.02$]. There was a significant interaction between the previous outcome and previous trial selection type [$F(1, 1102) = 508.63$, $p < .001$, $\eta_G^2 = 0.31$], between the previous outcome and target distance [F(2, 1102) = 31.81, p < .001, η_G^2 = 0.05], and between previous trial selection type and target distance [F(2, 1102) = 22.21, p < .001, η_G^2 = 0.41]. There were significant main effects of previous outcome [F(1, 1102) = 1618.31, p <.001, η_G^2 = 0.59], previous trial selection type [F(1, 1102) = 218.36, p < .001, η_G^2 = 0.16], and target distance [F(2, 1102) = 142.7, p < .001, η_G^2 = 0.20]. Figure 5.7 shows that participants are more likely to select the risky target if the previous trial was hit rather than missed (*cf* blue dot*s on the left with those* on the right). For the far target distance, participants were more likely to choose a risky target if their previous selection was safe than if it was risky even though they had hit the risky target successfully. This result suggest a balance between exploitation (reinforcing successful behaviours) and exploration (an increased risk towards selecting risky targets after successfully completing a previous action).

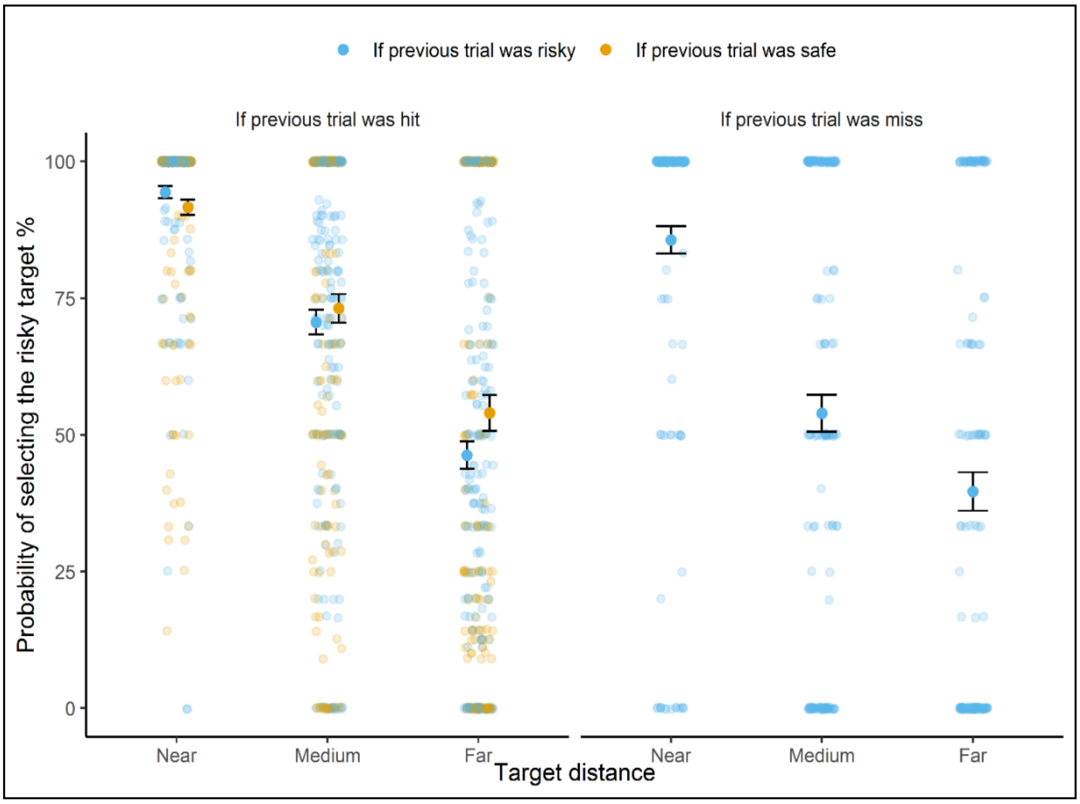

Figure 5.7 Probability of selecting the target compared to the previous riskiness behaviour as a function of target distance. Mean and standard error with dots as a single participant's observation. Blue dots show the observations when the previous trial selection was risky, and yellow dots are showing the observations when the previous trial selection was safe.

5.4.6 The risk switch threshold distance

One way of considering the group and individual differences in propensity to select the further 'risky' target is to conceptualise each participant as having a probability gradient where the probability of accepting the sensorimotor costs increases as the distance from the body increases. For simplification, this gradient can be thought of as linear in nature with a point where the probability is 50:50 (the risk switch threshold distance). The 'risk switch threshold distance' (i.e. the point beyond which participants were less likely to select the risky target) was calculated by conducting a logistic regression for each individual participant across the near, medium and far targets. The median threshold was found to be at 0.72 of arm span (Figure 5.8). Ten participants were removed from this analysis because they always selected the risky target (i.e. reached for the high reward target every trial). Figure 5.8 shows that there is a large degree of individual variability with regard to where the 'risk switch threshold distance' is located.

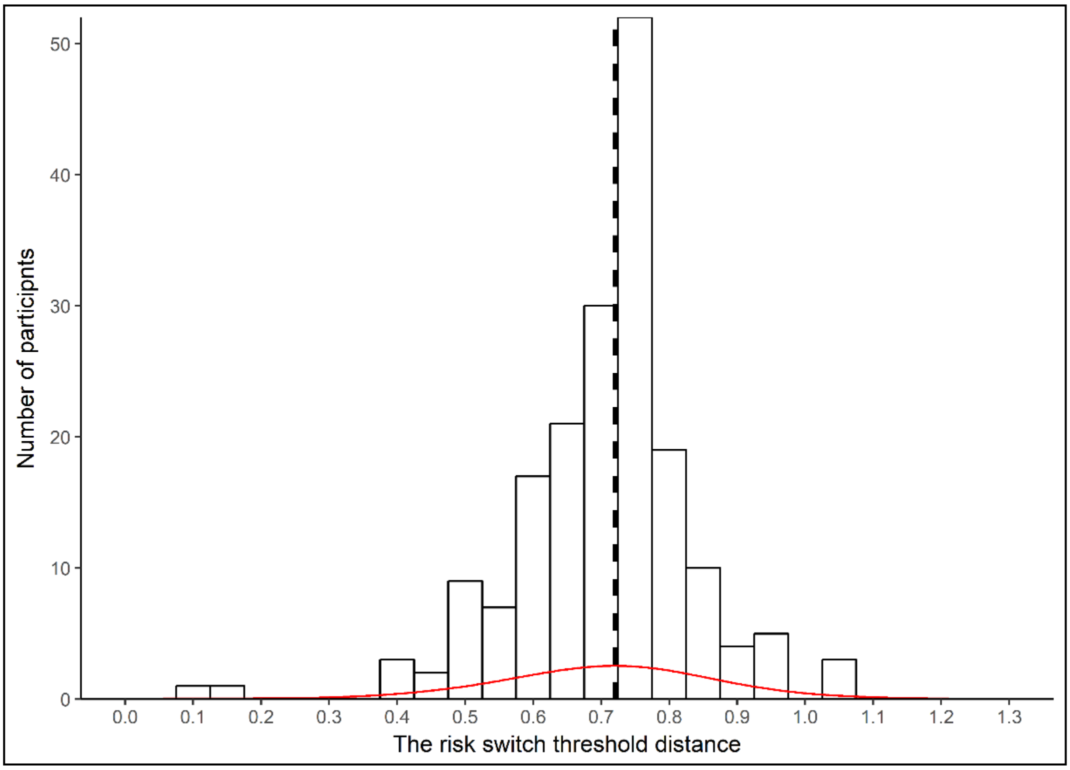

Figure 5.8 Density of the risk switch threshold distance, dashed line is the median threshold predicted (median = 0.72).

5.4.6.1 The risk switch threshold distance with gender

The 'risk switch threshold distance' was calculated for both gender (females and males) as in the previous section. The median threshold for females was found to be at 0.69 and males to be at 0.73 arm span (Figure 5.9). Figure 5.9 shows that there are group differences (on average) with regard to where the 'risk switch threshold distance' is located, but also note the great degree of overlap across these distributions.

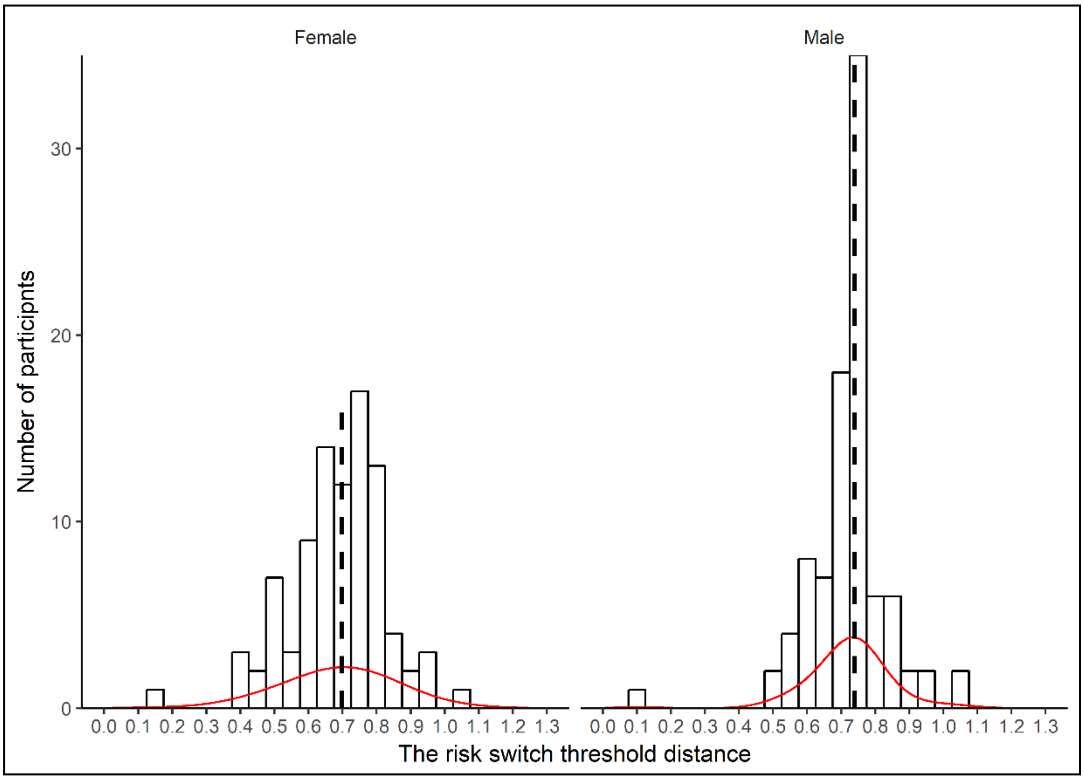

Figure 5.9 Density of the risk switch threshold distance (female is black; male is grey). Dashed lines are the median threshold predicted (black dashed line showing the female median at 0.69 and grey dashed line showing the male median at 0.73).

5.5 Kinematics across experiment 1 – 3

Kinematic data were analysed over 200 participants in the decision-making session. Movement duration was defined as the time taken to hit the selected target (i.e. high reward or low reward target) from the time the controller left the starting position. Trial duration was recorded from the time controller was on the starting position until the chosen target was hit. Reaction time was defined as the duration from starting position change colour (and whistle heard since both happened simultaneously) to controller movement from starting position. Therefore, movement duration was calculated as the difference between the trial reaction time and end of trial time (i.e. target hit).

5.5.1 Movement duration

A mixed ANOVA on the mean movement duration with gender (female and male), target distance (near, medium, far) and groups (control, motor noise, sensory noise) showed no significant interaction between the three factors [F(4, 388) = 1.15, p = .33, η_G^2 = 0.01]. The interaction between group and target distance was not significant [F(4, 388) = 0.54, p =.70, η_G^2 = 0.006], nor between gender and target distance [F(2, 388) = 0.29, p =.74, η_G^2 = 0.002], or between gender and group [F(2, 194) = 0.08, p = .91, η_G^2 = 0.001]. There was a main effect of target distance [F(2, 388) = 50.17, p < .001, η_G^2 = 0.20] with movements taking longer as target distance increased, but there was no main effect of group [F(2, 194) = 2.63, p = .07, η_G^2 = 0.02], nor gender [F(1, 194) = 0.96, p = .32, η_G^2 = 0.005] (Figure 5.10).

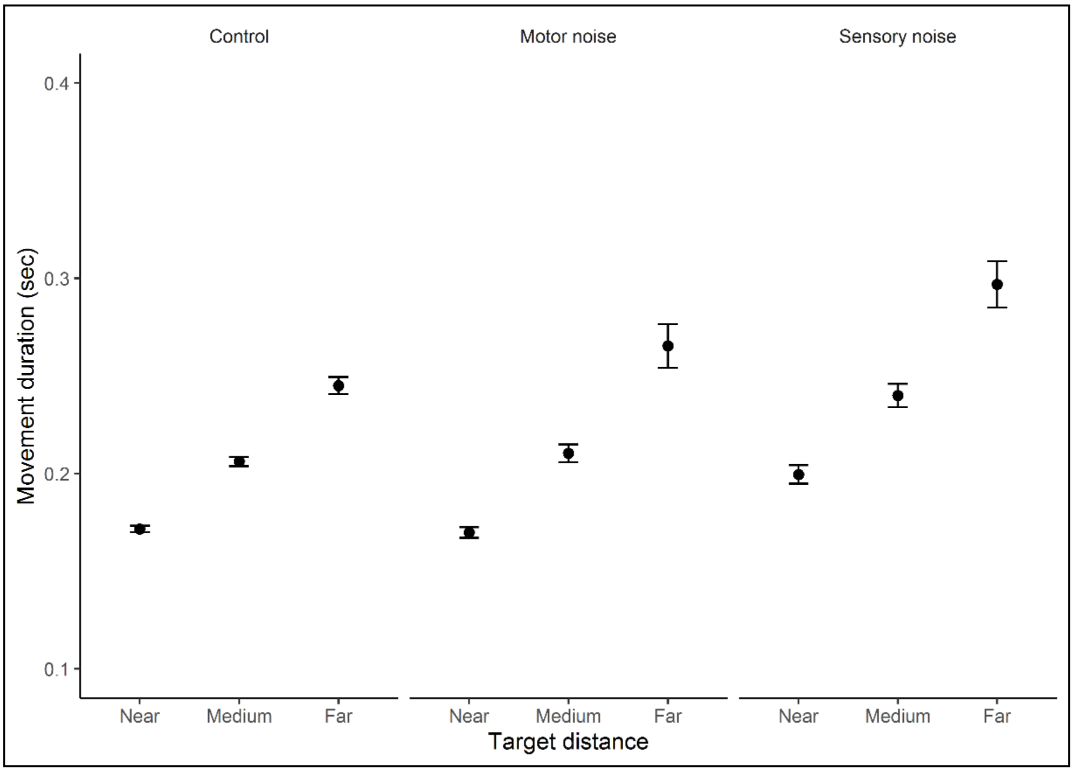

Figure 5.10 Mean movement duration (seconds) as a function of target distance (near, medium and far). The left hand panel shows the control group, middle one is the motor noise group and the right is the sensory noise group. Error bars represent standard error of the mean.

5.5.2 Movement duration over time for high and low reward hit in control group

A mixed model ANOVA on the mean movement duration for the high reward hits in the control group showed no significant interaction between target distance and trial number [$F(94, 4512) = 1.20$, $p = .09$, $\eta_G^2 = 0.02$]. There was a significant main effect of target distance [$F(2, 4512) = 7.60$, $p = .001$, $\eta_G^2 = 0.003$] but not trial number [$F(47, 2256) = 1.01$, $p = .45$, $\eta_G^2 = 0.02$]. A mixed model ANOVA on the mean movement duration for the low reward hits in the control group showed no significant interaction between target distance and trial number [$F(94, 4204) = 1.01$, $p = .45$, $\eta_G^2 = 0.02$]. There was a significant main effect of target distance [$F(2, 4204) = 333.71$, $p < .001$, $\eta_G^2 = 0.13$] and trial number [$F(47, 2102) = 1.68$, $p = .003$, $\eta_G^2 = 0.36$] with participants generally getting faster across time. This pattern is illustrated in Figure 4.10 but it is also clear from this visualisation that the effect seems to be most pronounced with far condition, where movements are slowest at their outset (Figure 5.11).

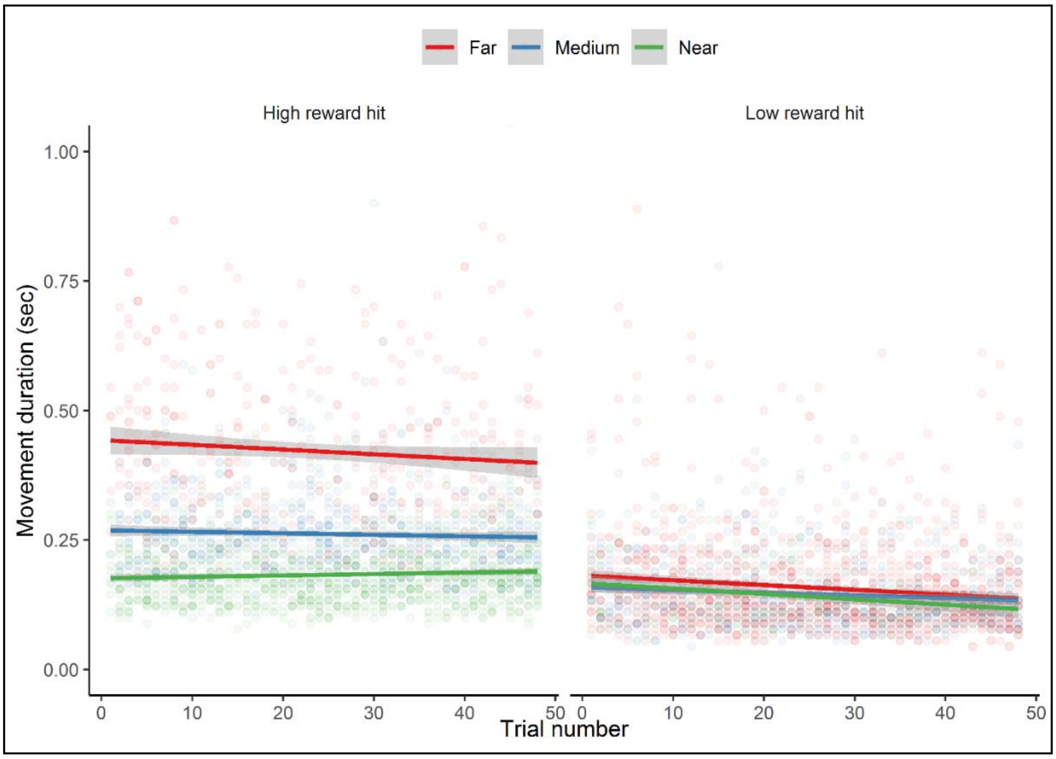

Figure 5.11 Movement duration in the control group plotted over trials (48 trials) with target distance (near; green, medium; blue, far; red). The left panel shows the high reward hit and the right panel shows the low reward hit trials.

5.5.3 Postural stability

Finally, we explored whether the effects were related in any way to the participant's postural abilities but there was no relationship between the target selection and any of our measures of postural stability as captured in the baseline assessments. We had reasoned that poor levels of postural stability at baseline (indexed by increased path length) would dampen risk seeking behaviour- with participants more averse to select tasks with greater demands on postural stability. This type of phenomenon is often observed in the sensorimotor literature, with compensatory strategies emerging – e.g. loss based selection (Gignac et al., 2002; Lang et al., 2002). However, contrary to these predictions, there was no relationship between any of the measures of stability captured by the experiment and task performance following corrections for multiple comparisons. Instead, the measures of postural stability showed the expected patterns whereby the posture was more stable with eyes open than with eyes closed. The oscillating room produced greater sway than either the eyes open or eyes closed condition.

5.6 Discussion

In Experiment 3 we repeated the task from Experiment 1, but this time manipulated sensory noise (whilst keeping the expected gain constant) by removing the virtual representation of the controller. The results were similar to those found in Experiment 2. We found the same selection frequencies as in Experiment 1, with males selecting the high reward target more often than females (although this was mediated by group and more evident in the control group than the sensory noise one), and participants less likely to select the high reward target as the target distance increased. It was shown previously that removing the visual feedback alter movement end-point location, misgudjung target distance, and increase the reaching path length (Keele & Posner, 1968; Goodbody & Wolpert, 1999; Prablanc & Péisson, 1990). The sensory noise manipulation had no effect, suggesting that participants were well-tuned to the sensorimotor costs associated with the increased perceptual noise. Once more, this was not possible to predict a priori as it might have been expected that the increased task difficulty would have pushed participants towards more conservative strategies. The fact that, again, the participants showed the same pattern of selection bias suggests strongly that adult humans are well tuned to the sensorimotor costs, and use these cost estimates when selecting between actions – rather than the more cognitively penetrable phenomenological experience of performance on the task.

It was possible to collapse the results of the first three experiments together (as increasing the reward in Experiment 1 had no impact on behaviour and because the motor noise and perceptual noise did not cause different selection strategies). This allowed us to explore the factors that biased the decision-making process across 200 participants. We established that there was not a bias to select a target on the basis of its laterality, or the laterality of the previous target. We did find that there was a bias for the participant to subsequently select a risky trial if the previous trial was safe, but this effect interacted with target distance such that it was negligible at near, moderate at the middle target distance, and largest for further targets. These results suggest there was a tendency towards exploration across the participants.

The usefulness of collecting these data in the virtual reality system was demonstrated by the wealth of kinematic data provided by the system. The kinematic data revealed the normal relationship between target distance and movement duration, and showed a tendency for participants to move slightly faster towards the safe target as the session progressed (presumably because of practice effects). Notably, there was no change in movement duration for the risky targets.

One critical question was how participants changed their behaviour in response to success or failure on the task. Notably, participants were more likely to select the risky target if the previous target was successfully hit than if it was missed. This finding suggests that participants update their estimates of the probability of success after each trial. The result of such updating is that participants will be more likely to select a previously successful trial type. This finding is consistent with models of decision-making developed in computer science – Partially Observable Markov Decision Processes (pom-dp). We tested whether a pom-dp would be able to capture the findings observed throughout these experiments, and found that the pom-dp was indeed able to produce the observed set of results (by Warburton et al. In Prep). A pom-dp model deals with the action selection problems where the environment is partially observable and appears in sequence. There are different elements of pom-dp; action, state, possible observations, and cost. The model makes the prediction that participants should shift towards selecting the 'risky' target over time (with this effect being most notable at the furthest distance target as this target starts being selected reasonably infrequently). The model was able to capture the gender differences we observed but it did not reveal any differences between the values attached to the values of the rewards, sensorimotor costs or selection biases. Instead, it appeared that the males as a group had a disposition towards risk (i.e. a further 'risk switch threshold distance')– a disposition that has been reported consistently throughout the research literature. The prediction from the pom-dp is that the gender differences should disappear over repeated sessions of the task (because all participants show a bias to update the probability estimates of success – which would lead to the further 'risky' target being selected as frequently as the middle and close distances over time removing any population differences). We tested these predictions in the fourth experiment.

Having identified that increasing motor and sensory noise did not have a substantial impact on choice selection at a group level averaged across trials, we sought to understand the strategies employed by participants across all three experiments and explore what factors might be biasing influence trial-by-trial selection. To this end, we collapsed across Experiments 1 – 3 (control group, motor noise group, and sensory noise group) and this provided a sample of 200 participants and allowed us to probe the influence of target location, previous target selection, and previous trial success rate on choice selection from these aggregated datasets.

We were also interested in selection bias. Examining this across all Experiments is possible due to the similar nature of the paradigms, and affords a much larger number from which to make conclusions. In this chapter we present the biases result in the previous three experiments and the model used to explain the data.

CHAPTER 6: REPETITION EFFECT ON DECISION-MAKING (EXPERIMENT 4)

6.1 Introduction

The first three experiments all involved participants selecting the target under conditions where the task was entirely novel. In this experiment, we were interested in exploring how the selection choice changed over time. The modelling of the first three experiments showed that the data were well described by a Partially Observable Markov Decision Process (pom-dp). The pom-dp model assumed that participants update their estimates of probable success after they complete a trial (so increase the probability estimate of a hit after a successful trial and vice versa). The results of Expriments 1 – 3 show that participants successfully hit the 'risky' target more often than not. Thus, the pom-dp model suggests that participants should become increasingly biased towards the risky target over time. This effect would be expected to be particularly pronounced for the furthest target (as this was selected less frequently in the first three experiments). The pom-dp model suggests that ultimately the effects of target distance should dissipate over repeated trials – and the effect of gender (whereby males show riskier behaviour than the females) should ultimately disappear. In the fourth experiment we examined the effect of repeating the task over a series of sessions on the riskiness behaviour of participants to test the predictions of the pom-dp model.

The aim of this experiment was to examine the effect of task repetition on the decision making. We hypothesised that participants would always reach to the high reward target in the last session of the experiment.

6.2 Methods

6.2.1 Participants

Twenty adults (10 male; 9 right handed and 10 female; 10 right handed) from the University of Leeds participated in this study (mean age = 23 years, SD = 3.3). All participants gave their written informed consent, and the experiment complied with the ethical guidelines approved by the University of Leeds ethical committee (ethical approval number: 17-0181, date approved: 16/06/2017).

6.2.2 The task design

Participants visited the lab six times over three consecutive days (one visit in the morning and one visit in the afternoon each day). Each visit consisted of three blocks, with participants completing eighteen blocks in total. The first block had three sessions; a practice session, a baseline session, and decision-making session as described in the general methods section (81 trials in total). For the remaining seventeen blocks, participants completed only a practice session and a decision-making session (54 trials in total) (Panel B Figure 6.1). The task was to move a controller held in the preferred hand to hit the target. The controller position was tracked and a virtual representation of the controller was visible throughout the experiment. The total points obtained were reported to the participants after each block and they were encouraged to increase their score in the next block. The experiment configuration was low reward target (one star) vs high reward target (three star). As in the previous Experiments, the high reward targets were positioned at one of three distances from the starting position (0.50, 0.65 or 0.75 arm span). The low reward target was always positioned at 0.35 arm span (Panel A Figure 6.1). This produced a 2 (gender: female, male; between subjects) x 3 (target distance: near, medium, far; within subjects) x 18 (block number: 1:18; within subjects) design.

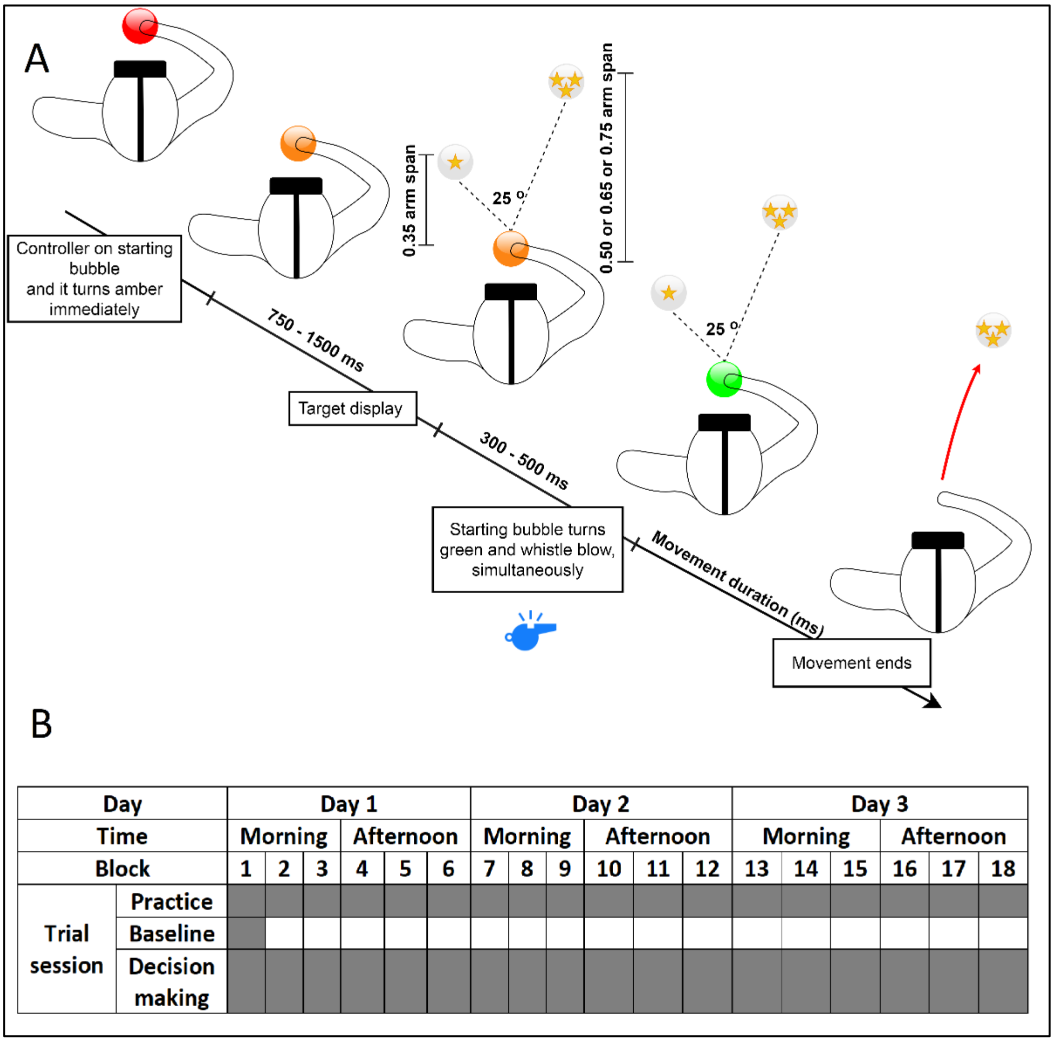

Figure 6.1 Panel A participant from above in the decision-making session where the closer target (one star) appears at 0.35 arm span and the further target (three stars) appears at either 0.50 or 0.65 or 0.75 arm's span with an angular separation of 25°. The lower line represents the sequence of the trial; from the participant landing on the start position (red target) to hearing the whistle (signal to move). Panel B shows the days, blocks, and trial sessions for each visit (grey cells the session took place and white cells there is no session).

6.3 Results

Before conducting any inferential statistics, data were examined for violations of assumptions of normality through box- plots, Q–Q plots, histograms and Shapiro–Wilk test ($P < 0.05$), with transformations performed where necessary. A Z-score was calculated and ± 3 were assigned as a threshold to deal with outliers.

6.3.1 Points obtained

A mixed model ANOVA on the points obtained revealed that there was no significant three way interaction between target distance, gender, and block number [$F(2, 710) = 0.06$, $p = .93$, $\eta_G^2 = 0.001$]. There was a significant interaction between target distance and block number [$F(2, 710) = 5.15$, $p = .006$, $\eta_G^2 = 0.005$], showing that the effect of distance decreased as block number increased and between gender and target distance [$F(2, 710) = 3.99$, $p = .01$, $\eta_G^2 = 0.04$]. There was no significant interaction between gender and block number [$F(1, 355) = 1.67$, $p = .19$, $\eta_G^2 = 0.002$]. There was a significant main effect of target distance [$F(2, 710) = 14.54$, $p < .001$, $\eta_G^2 = 0.01$] with fewer points being obtained as distance increased, suggesting the participants were less likely to go for high reward target in these trials, and block number [$F(1, 355) = 100.65$, $p < .001$, $\eta_G^2 = 0.14$] with participants accruing more points across time, and gender with males accuring more points than females [$F(1, 355) = 4.87$, $p = .02$, $\eta_G^2 = 0.008$]. Figure 6.2 shows average points obtained from each target distance divided by gender.

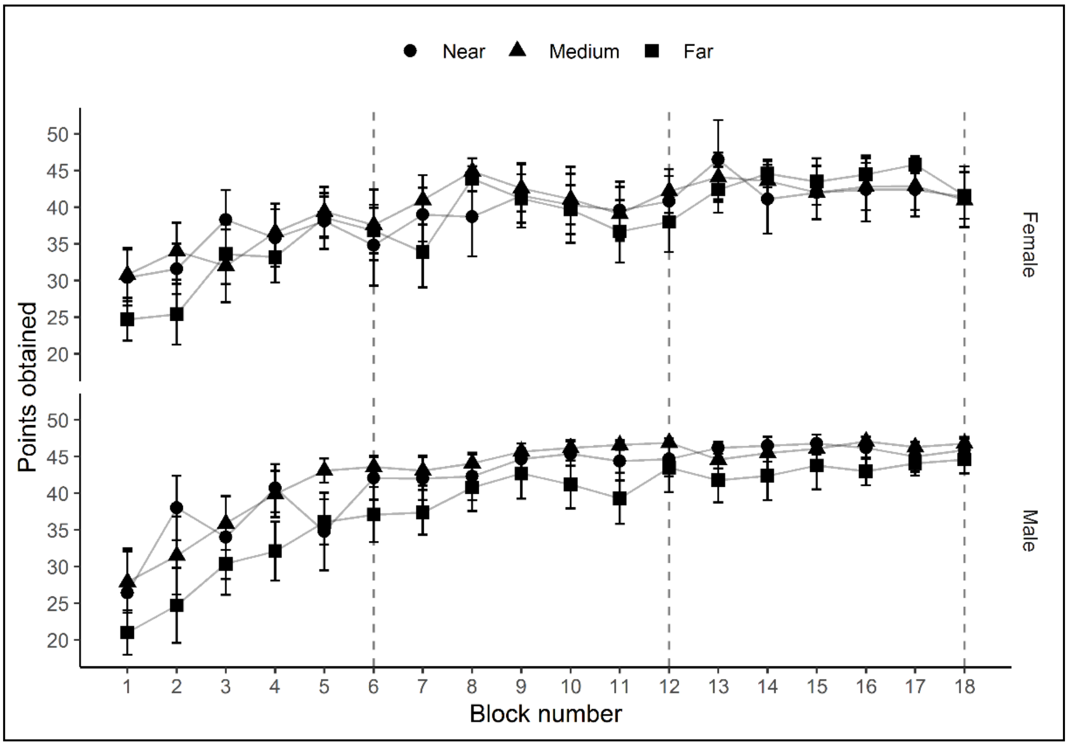

Figure 6.2 Average number of points obtained for females (upper panel) and males (lower panel) across blocks (with standard error bars) for each target distance (near; circle, medium; triangle, far; square). Dashed lines represent the end of each day.

6.3.2 High reward target selection

A mixed model ANOVA on the high reward target selection showed that there was no significant three way interaction between target distance, gender, and block number [F(2, 710) = 2.07, p = .12, η_G^2 = 0.002]. There was a significant interaction between target distance and block number [F(2, 710) = 20.37, p < .001, η_G^2 = 0.02], and between gender and target distance [F(2, 710) = 0.47, p = .60, η_G^2 = 0.0006]. There was a significant interaction between gender and block number [F(1, 355) = 4.34, p = .03, η_G^2 = 0.006]. There was a significant main effect of target distance [F(2, 710) = 61.3, p < .001, η_G^2 = 0.07], block number [F(1, 355) = 85.5, p < .001, η_G^2 = 0.11], but not for gender [F(1, 355) = 0.40, p = .52, η_G^2 = 0.0006]. Figure 6.3 shows average high reward target selection for each target distance divided by gender.

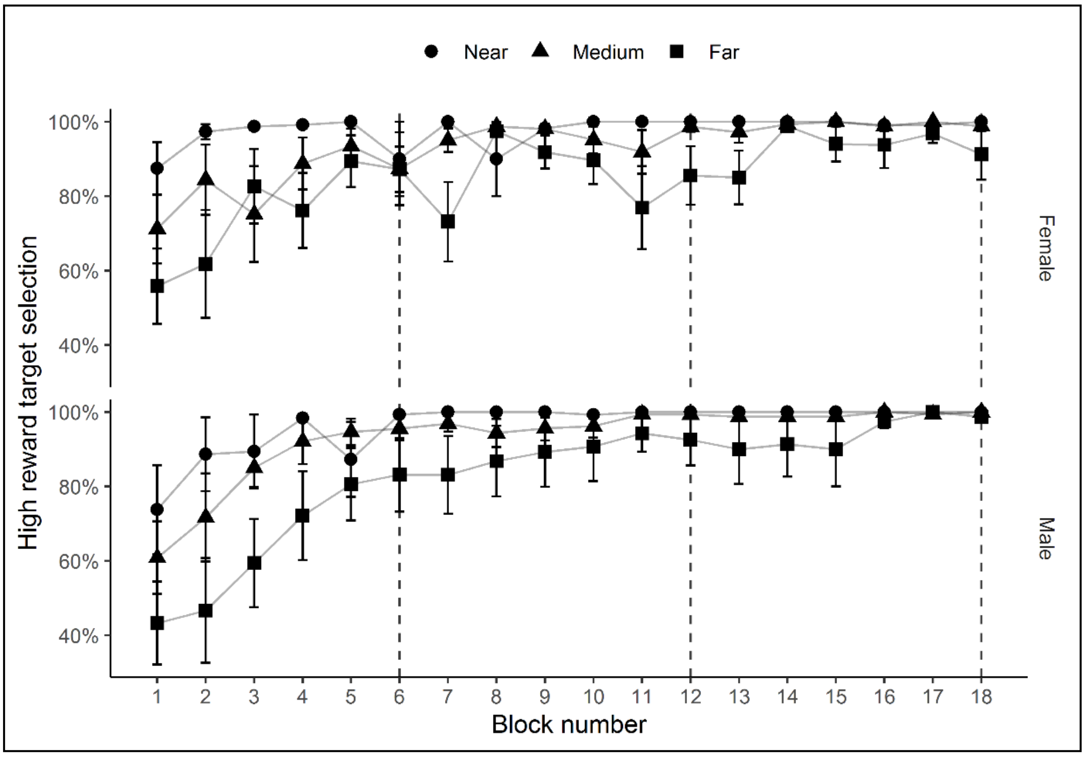

Figure 6.3 Percentage of high reward target selection for females (upper panel) and males (lower panel) across blocks (with standard error bars) for each target distance (near; circle, medium; triangle, far; square). Dashed lines represent the end of each day.

6.3.3 High reward target hit

A mixed model ANOVA on the high reward target hit showed that there was no significant three way interaction between target distance, gender, and block number [F(2, 710) = 0.41, p = .66, η_G^2 = 0.0006]. There was a significant interaction between target distance and block number [F(2, 710) = 7.14, p < .001, η_G^2 = 0.009], and between gender and target distance [F(2, 710) = 5.48, p = .004, η_G^2 = 0.007]. There was a significant interaction between gender and block number [F(1, 355) = 4.95, p = .02, η_G^2 = 0.007]. There was a significant main effect of target distance [F(2, 710) = 16.62, p < .001, η_G^2 = 0.02], block number [F(1, 355) = 64.43, p < .001, η_G^2 = 0.08], but not for gender [F(1, 355) = 1.02, p = .31, η_G^2 = 0.001]. Figure 6.4 shows high reward target hit for each target selection divided by gender.

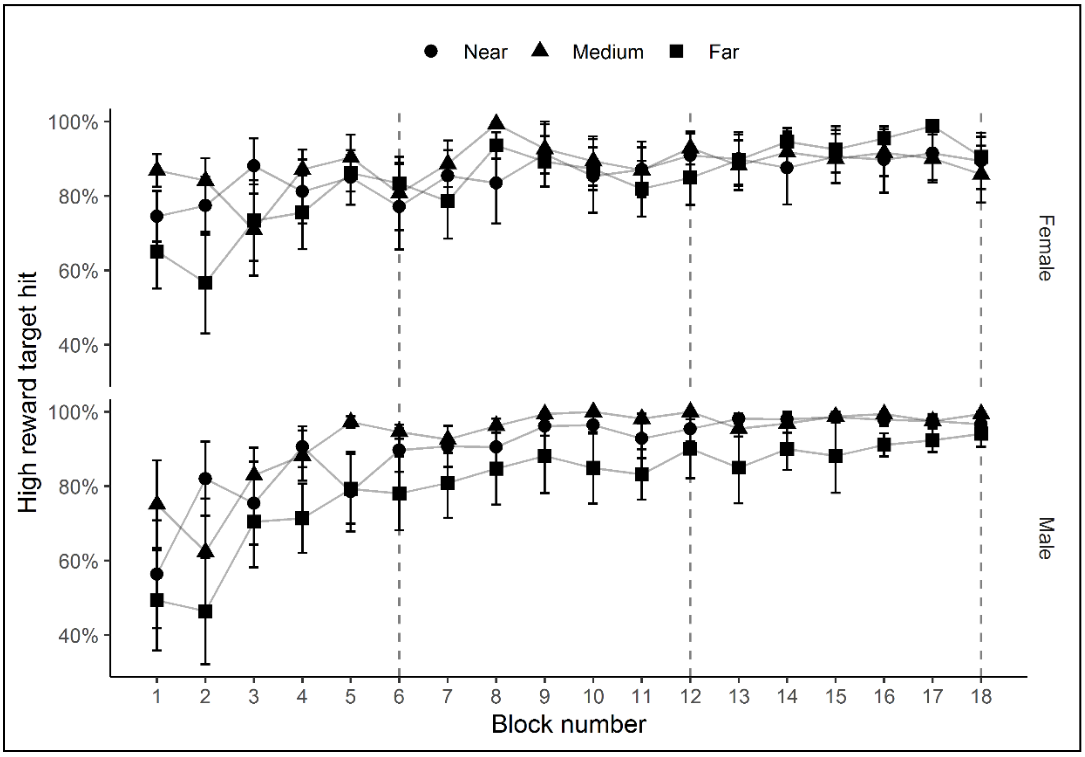

Figure 6.4 Percentage of high reward target hits for females (upper panel) and males (lower panel) across blocks (with standard error bars) for each target distance (near; circle, medium; triangle, far; square). Dashed lines represent the end of each day.

6.3.4 High reward target selection and points obtained difference between the first and last visit

High reward target selection and points obtained averaged across the first visit (1st, 2nd, and 3rd block) and across the last visit (16th, 17th, and 18th block) and analysed. A mixed model ANOVA on the high reward target selection showed no significant three way interaction between gender, visit, and target distance [F(2, 72) = 1.27, p = .28, η_G^2 = 0.009]. There was a significant interaction between the visit and target distance [F(2, 72) = 13.48, p < .001, η_G^2 = 0.08], but not with gender and target distance [F(2, 72) = 0.33, p = .71, η_G^2 = 0.002], nor with gender and visit [F(1, 36) = 1.45, p = .23, η_G^2 = 0.02]. There was a significant main effect of target distance [F(2, 72) = 21.09, p < .001, η_G^2 = 0.13], and of visit [F(1, 36) = 21.85, p < .001, η_G^2 = 0.31], but no main effect of gender [F(1, 36) = 0.67, p = .41, η_G^2 = 0.01]. Figure 6.5 shows high reward target selection from each target distance averaged across the first and last visit. The accumulation of the data at the last visit around 100% is due to the ceiling effect observed as participants selected the high reward target with time.

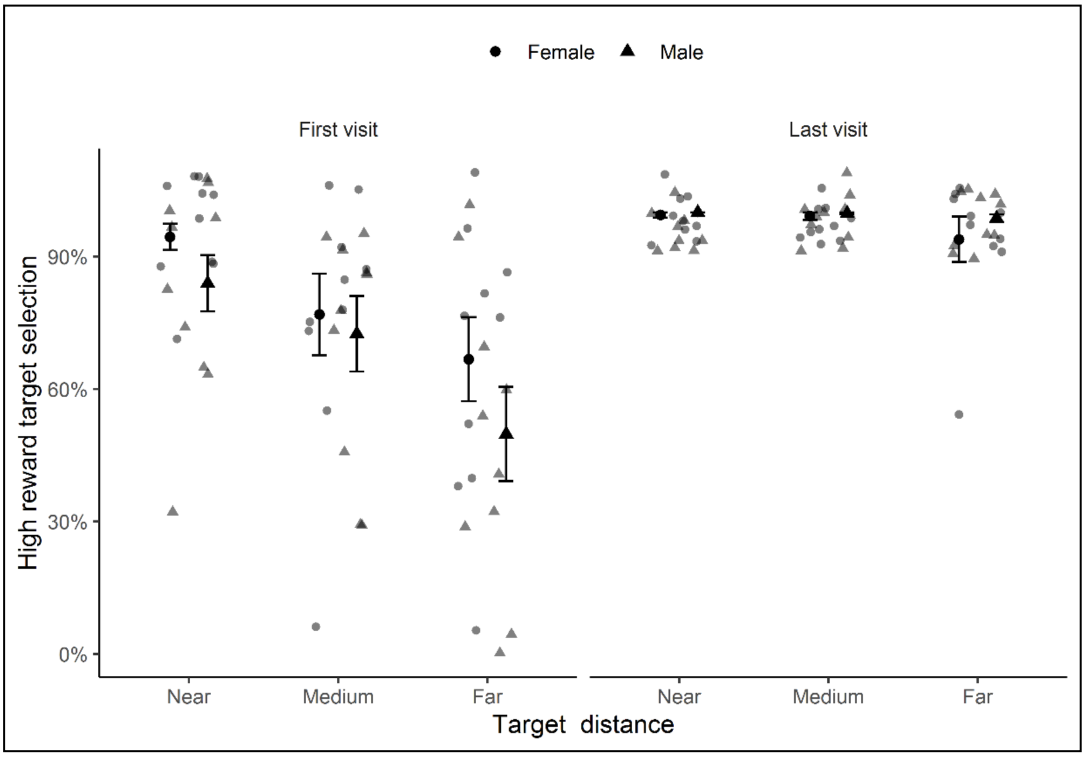

Figure 6.5 Percentage of high reward target selection across the first visit (left panel) and across the last visit (right panel) fir dender (female; circle, male; triangle) with mean and standard error for each target distance (near, medium, far).

A mixed model ANOVA on the points obtained showed no significant three way interaction between gender, visit, and target distance [F(2, 72) = 0.11, p = .89, η_G^2 = 0.008]. There was no significant interaction between the visit and target distance [F(2, 72) = 3.09, p = .05, η_G^2 = 0.02], nor between gender and target distance [F(2, 72) = 0.85, p = .43, η_G^2 = 0.006], or with gender and visit [F(1, 36) = .56, p = .45, η_G^2 = 0.01]. There was a significant main effect of target distance [F(2, 72) = 3.44, p = .03, η_G^2 = 0.02], and of visit [F(1, 36) = 26.77, p < .001, η_G^2 = 0.35], but no main effect of gender [F(1, 36) = 0.07, p = .78, η_G^2 = 0.001]. Figure 6.6 shows points obtained from each target distance averaged across the first and last visit.

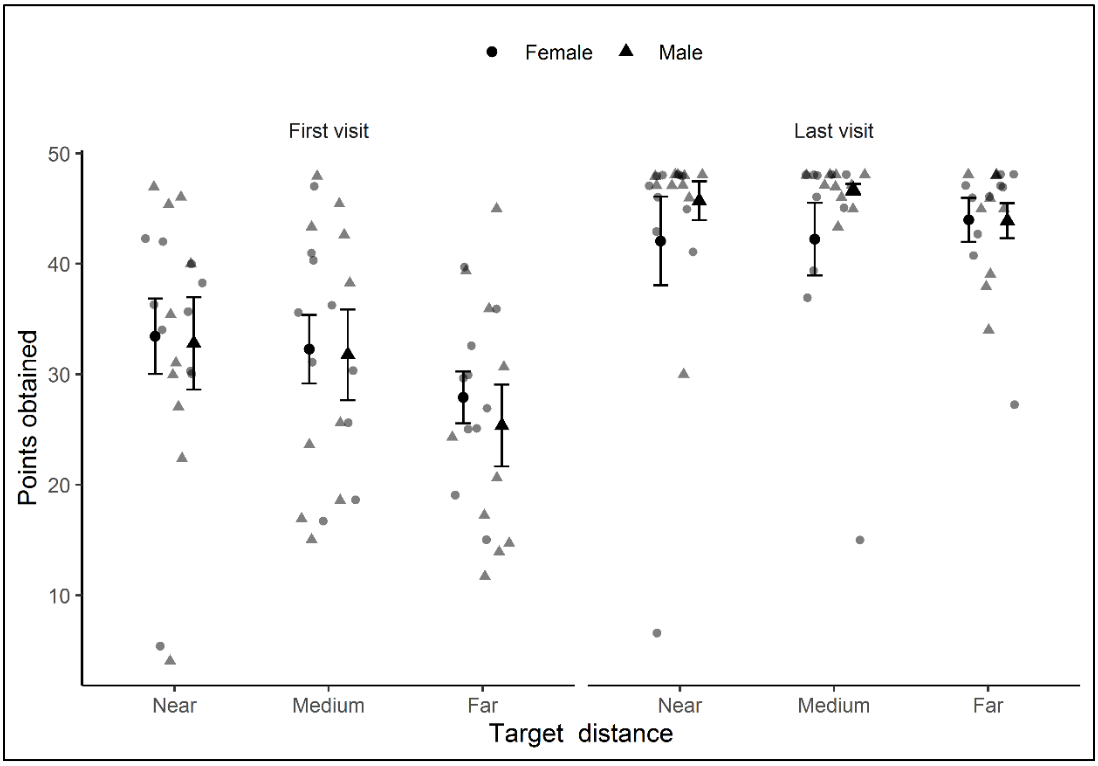

Figure 6.6 Average points obtained across the first visit (left panel) and across the last visit (right panel) fir dender (female; circle, male; triangle) with mean and standard error for each target distance (near, medium, far).

6.4 Discussion

The Partially Observable Markov Decision Process model predicted that participants would become increasingly likely to select the 'risky' further target as they undertook the task over repeated sessions. The reason for this prediction is that the model updates its probability estimate after each trial so that a successful hit causes the system to increase its estimate of success and this results in the same target having an increased probability of being selected on future trails. This prediction was borne out by the data. One consequence of this long term effect would be to remove the gender differences observed when participant groups are first introduced to the task. This prediction was also borne out by the data. It can be concluded that the behaviour observed in the first four experiments are well predicted by a Partially Observable Markov Decision Process model. The implication of this conclusion is that adult humans combine the rewards and sensorimotor costs when determining the relative value of targets in a binary selection task. The sensorimotor costs are continually updated on the basis of performance. This simple notion can explain well the behaviours observed across the first four experiments within this thesis.

CHAPTER 7: DYNAMIC DECISION MANIPULATION (EXPERIMENT 5)

7.1 Introduction

The first four experiments described in this thesis always provided participants with a consistent choice – whether to reach for the ‘safe’ target (which was continually visible and not timed out) or to reach for the ‘risky’ target (albeit that the ‘risky’ target had different sensorimotor costs on a trial-by-trial basis). In Experiment 5, we set out to explore decision-making in a more dynamic context where both target choices would time out and where the choice was not simply between ‘low reward-sensorimotor cost’ versus ‘high reward-sensorimotor cost’. In the fifth experiment, a variety of trials were presented where participants needed to determine the cost-reward ratio in order to make their selection. This allowed us to explore whether participants defaulted to simple heuristics (select the highest reward or select the lowest sensorimotor costs) or whether they combined the rewards and sensorimotor costs (as found in the first three experiments).

The hypothesis of this experiment was that participants would combine the sensorimotor cost and target reward in their decision making process as shown in the previous experiments.

7.2 Methods

7.2.1 Participants

Forty adults (20 males; 19 right handed and 20 females; 19 right handed) from the University of Leeds participated in this study (mean age = 25.1 years, SD = 6.8). All participants gave their written informed consent, and the experiment complied with the ethical guidelines approved by the University of Leeds ethical committee (ethical approval number: PSC-416, date approved: 07/09/2018).

7.2.2 The task design

Participants undertook three sessions: a practice session, a baseline session, and decision-making session as described in the general methods section. There were 6 trials in the practice session, 12 trials in the baseline session, and 24 trials in the decision-making session. The participant's task was to move a controller held in the preferred hand to hit the target. The controller position was tracked and a virtual representation of the controller was visible throughout the experiment.

The experiment configuration used a low reward target (one star) and a high reward target (two star). The targets appeared in three possible distances (either 0.50, 0.65 or 0.75 arm span). In the decision-making session, the two targets appeared in three possible combinations: *reward advantage* (both targets at the same distance: 0.50; 0.65; 0.75 but one target worth twice as much as the other); *distance advantage* (targets both worth one star and configured as 0.50-0.65; 0.65-0.75; 0.50-0.75); *mixed* (one star target at 0.5 vs two star target at 0.65; one star target at 0.65 vs two star target at 0.75; one star target at 0.5 vs two star target at

0.75) (Panel A, B and C in Figure 7.1) . The targets were presented in a random order but the same random order was used for all participants so we could compare like-with-like when looking at the effects of age.

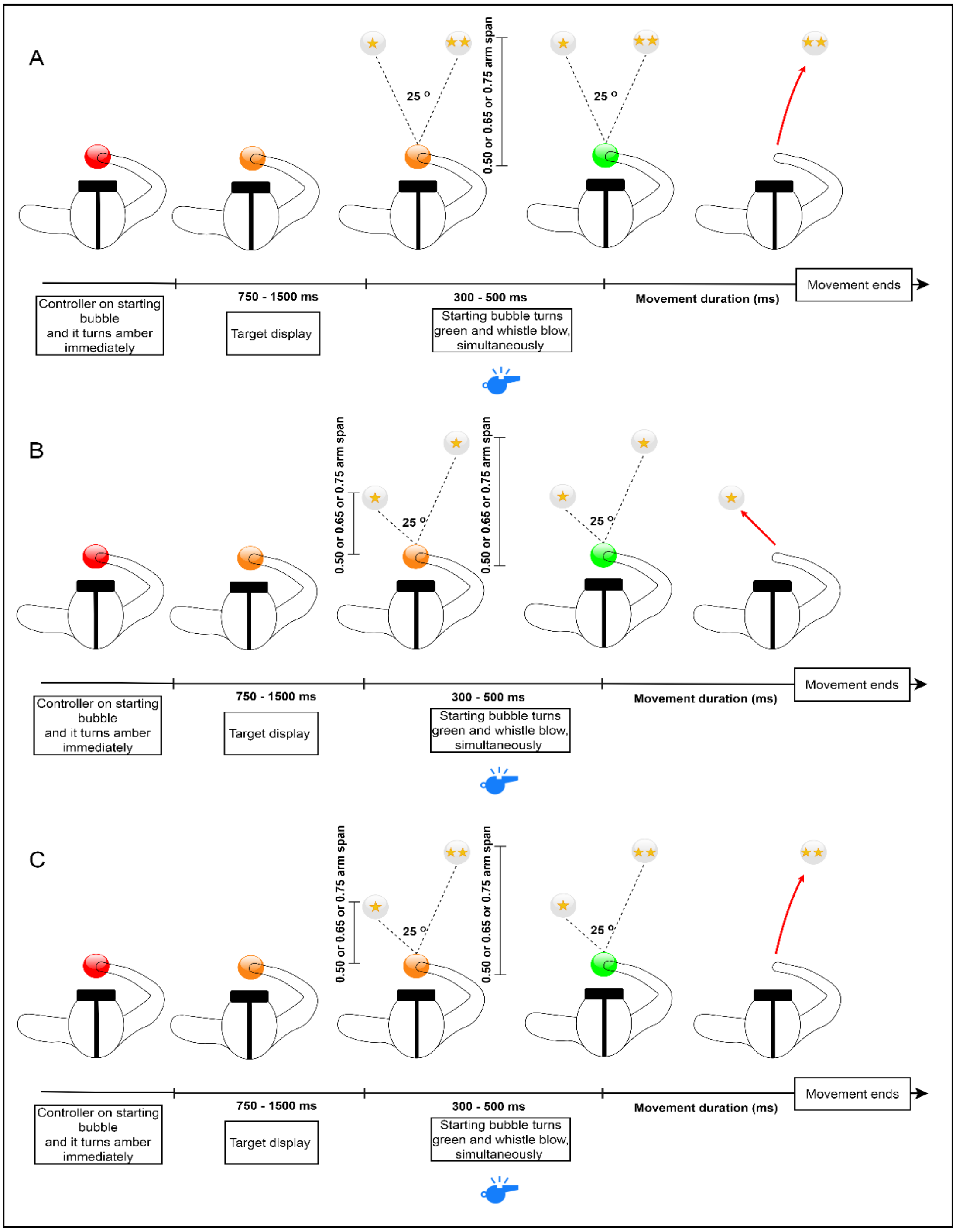

Figure 7.1 Panel A shows participant from above in the decision-making session for the reward advantage trial types, panel B shows the distance advantage trial type and panel C shows the mixed trial type (see text for details). The lower line represents the sequence of the trial; from the participant landing on the start position (red target) to hearing the whistle (signal to move).

This produced a 2 (gender: female, male; between subjects) x 3 (trial configurations: reward advantage, distance advantage, mixed; within subjects) x 6 (target selected: high reward, low reward, closer distance, further distance, low reward and closer distance, high reward and further distance; within subjects) x 4 (disparity size: same, small, medium, large; within subject) design.

Disparity size is determined by the sensorimotor cost associated with targets but where the cost is assumed to grow in a non-linear fashion with increasing distance (thus the cost differential is higher between the furthest and middle distance target than between the middle distance and closest target). Therefore if a target is at 0.50 and the other target is at 0.65 then the sensorimotor disparity is relatively small; if a target is at 0.65 and the other target is at 0.75 then the sensorimotor disparity will be medium, and finally when a target is at 0.50 and the other target is at 0.75 then the sensorimotor disparity will be large. The disparity size is the same when there is no sensorimotor cost difference between the two targets (i.e. both of them at the same distance). Table 7.1 shows the various target configurations with the disparity size.

Table 7.1 Trial configuration for each target combination. The number in each cell refers to the distance as a proportion of arm span, and number of stars is given in parentheses. The final column categorises the magnitude of the functional difference in reach distance (same, small, medium or large). The disparity size refers to the difference in sensorimotor costs where the furthest target has the greatest risk of falling. This means that the risk difference is greater between the medium and furthest target than the nearest and medium ones (despite the distance difference being equal).

Trial configuration	Target 1	Target 2	Disparity size
Reward Advantage	0.5 (1)	0.5 (2)	same
	0.5 (2)	0.5 (1)	same
	0.65 (1)	0.65 (2)	same
	0.65 (2)	0.65 (1)	same
	0.75 (1)	0.75 (2)	same
	0.75 (2)	0.75 (1)	same
Distance Advantage	0.5 (1)	0.65 (1)	small
	0.65 (1)	0.5 (1)	small
	0.65 (1)	0.75 (1)	medium
	0.75 (1)	0.65 (1)	medium
	0.5 (1)	0.75 (1)	large
	0.75 (1)	0.5 (1)	large
Mixed	0.5 (1)	0.65 (2)	small
	0.65 (2)	0.5 (1)	small
	0.5 (1)	0.65 (2)	small
	0.65 (2)	0.5 (1)	small
	0.65 (1)	0.75 (2)	medium
	0.75 (2)	0.65 (1)	medium
	0.65 (1)	0.75 (2)	medium
	0.75 (2)	0.65 (1)	medium
	0.5 (1)	0.75 (2)	large
	0.75 (2)	0.5 (1)	large
	0.5 (1)	0.75 (2)	large
	0.75 (2)	0.5 (1)	large

7.3 Results

Before conducting any inferential statistics, data were examined for violations of assumptions of normality through box- plots, Q–Q plots, histograms and Shapiro–Wilk test ($P < 0.05$), with transformations performed where necessary. A Z-score was calculated and ± 3 were assigned as a threshold to deal with outliers. There were four trial outcomes in the experimental session: hit when the participants reached the target on time, miss when the participant did not reach the target on time, premature when they reached too early, and no-go when they did not move at all. For reasons of clarity and interest we examined only which target was selected. Table 7.2 shows the percentage of each possible outcome.

Table 7.2 Percentage of trial outcomes with mean and standard deviation (SD).

Trial outcome	Mean (%)	SD (%)
Hit	74.47	1.26
Miss	18.22	2.54
Premature	2.70	6.60
No-go	4.58	5.08

7.3.1 Reward advantage trial configuration

Repeated measure ANOVA showed no significant interaction between gender and target selected [$F(1, 38) = 0.37$, $p = .54$, $\eta_G^2 = 0.01$]. There was a main effect of target selected with participants selecting the high reward target more often than the low reward target [$F(1, 38) = 276.96$, $p < .001$, $\eta_G^2 = 0.87$] but no main effect of gender [$F(1, 38) = 0.97$, $p = .32$, $\eta_G^2 = 0.01$] (Figure 7.2).

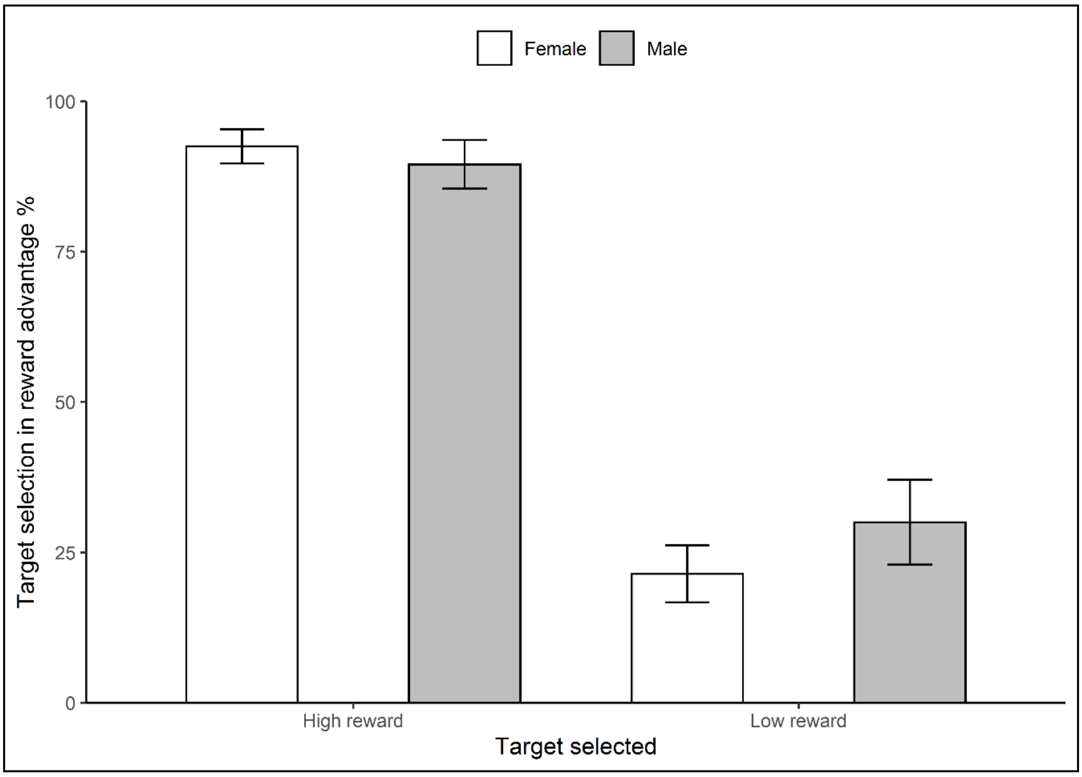

Figure 7.2 Target selection percentage in the reward advantage trial configuration for females (unfilled bars) and males (filled bars) at each target selected (high reward and low reward). Error bars show standard error of the mean.

7.3.2 Distance advantage trial configuration

Repeated measure ANOVA showed no significant interaction between gender and target selected [F(1, 38) = 0.09, p = .76, η_G^2 = 0.002]. There was a main effect of target selected with participants selecting the closer distance target more often than the further distance target [F(1, 38) = 424.37, p < .001, η_G^2 = 0.91] but not gender [F(1, 38) = 0.97, p = .32, η_G^2 = 0.01] (Figure 7.3).

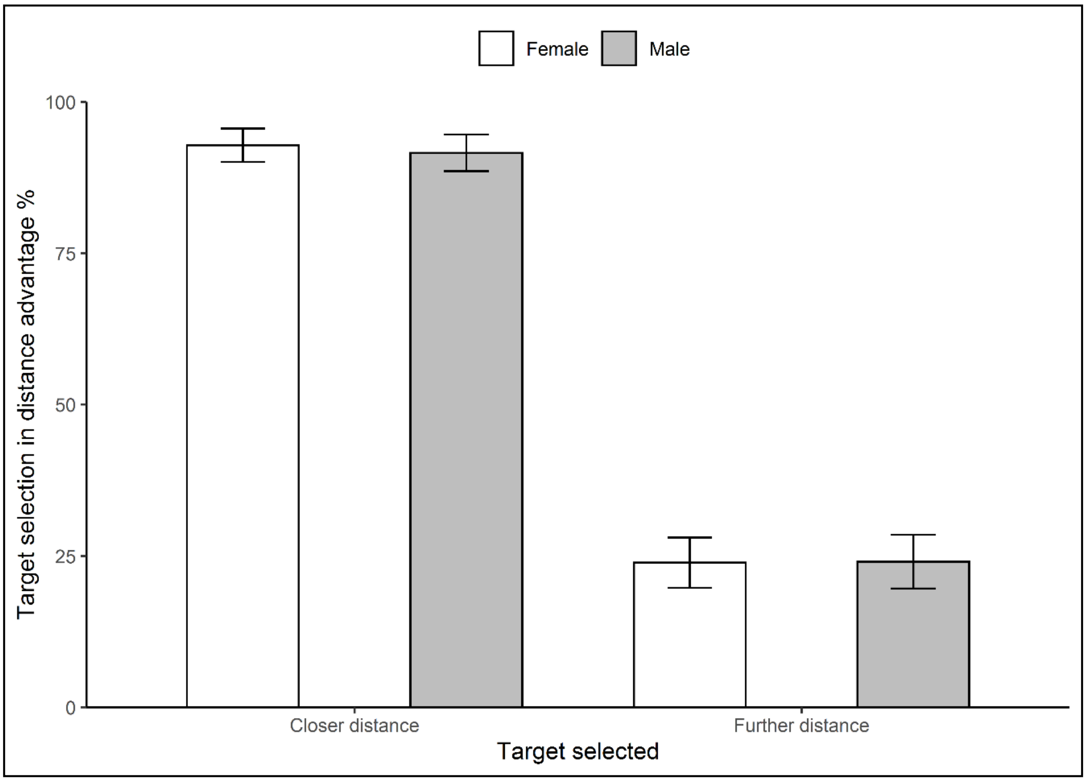

Figure 7.3 Target selection percentage in the distance advantage trial configuration for females (unfilled bars) and males (filled bars) at each target selected (closer distance and further distance). Error bars show standard error of the mean.

We explored whether the magnitude of the difference between the nearer and further target (disparity size) had an effect on selection. A repeated measure ANOVA revealed no significant two way interaction between the target selected and disparity size [F(2, 111) =1.52, p = .22, η_G^2 = 0.001]. There was a main effect of target selected where participants selected the closer distance target more often compared to the further distance targets [F(1, 111) = 485.38, p < .001, η_G^2 = 0.75], but no main effect of disparity size [F(2, 111) = 0.12, p = .88, η_G^2 = 0.02].

7.3.3 Mixed trial configuration

Repeated measure ANOVA showed no significant interaction between gender and target selected [F(1, 38) = 0.47, p = .49, η_G^2 = 0.02]. There was no main effect of target selected [F(1, 38) = 2.49, p =.12, η_G^2 = 0.003] nor of gender [F(1, 38) = 0.51, p = .47, η_G^2 = 0.06] (Figure 7.4).

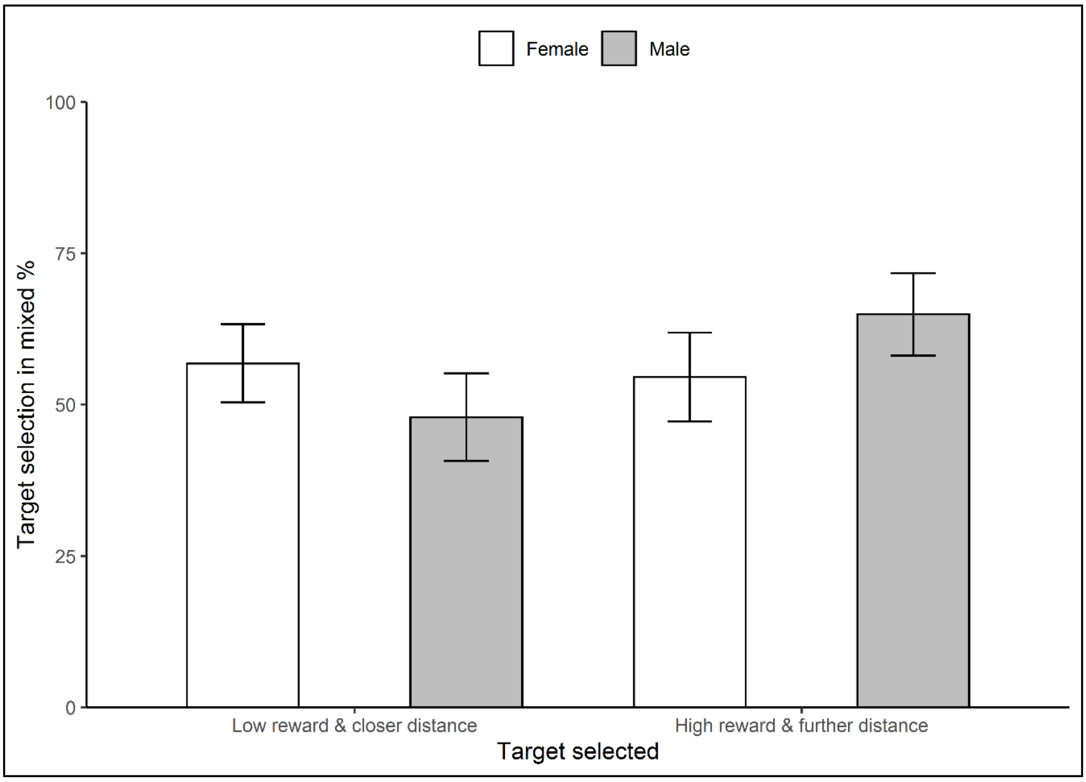

Figure 7.4 Target selection percentage in the mixed trial configuration for females (unfilled bars) and males (filled bars) at each target selected (low reward & closer distance and high reward & further distance). Error bars show standard error of the mean.

We explored whether the magnitude of the difference between the nearer and further target had an effect on selection. A repeated measure ANOVA revealed a significant two way interaction between the choice and disparity size [F(2, 115) =6.51, p = .002, η_G^2 = 0.14]. There was a main effect of target selected [F(1, 115) = 5.94, p = .01, η_G^2 = 0.01], and main effect of disparity size [F(2, 115) = 6.51, p = .002, η_G^2 = 0.09] (Figure 7.5).

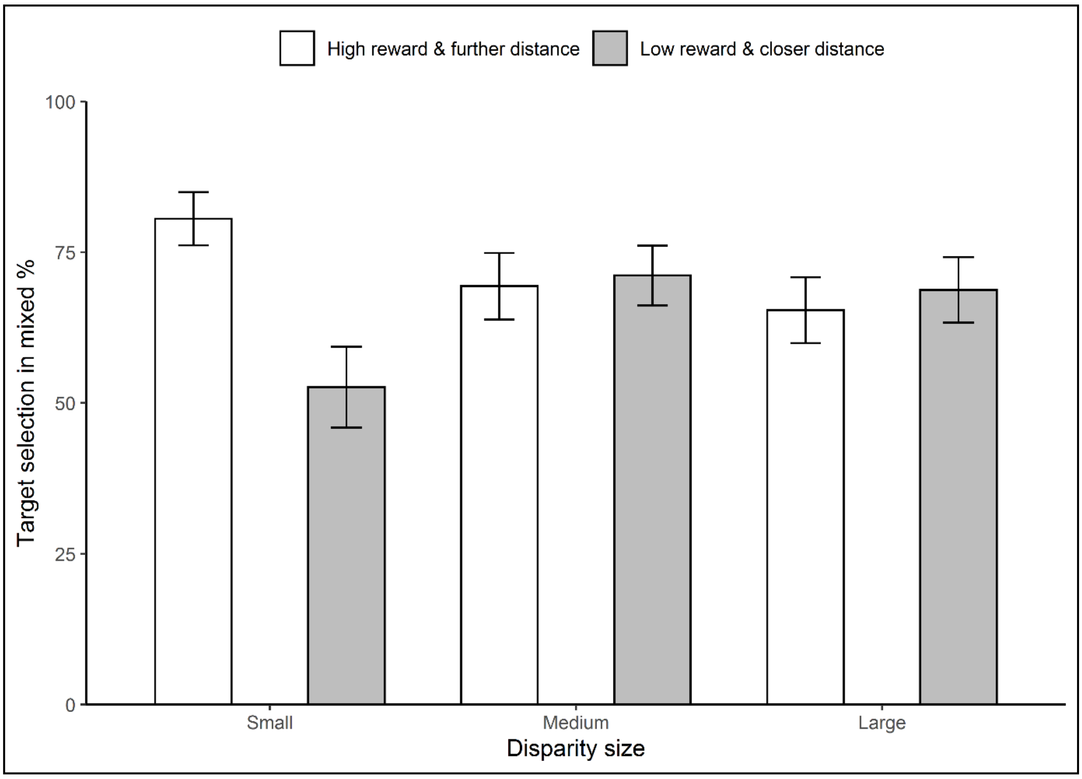

Figure 7.5 Target selection percentage in the mixed trial configuration as a function of the disparity size (small, medium, and large). Filled bars showing the lower point and closer distance targets and unfilled bars are the higher point and further distance targets. Error bars show standard error of the mean.

7.4 Discussion

In the fifth experiment, we examined how participants selected targets when they needed to make dynamic decisions between different targets (i.e. there was no consistent 'safe' target). The results showed clearly that the participants were biased towards targets with lower sensorimotor costs. The results showed equally clearly that the participants were biased towards targets with higher rewards. Nevertheless, neither sensorimotor costs nor rewards completely dominated the decision-making process. If sensorimotor cost differences were small then there was a bias towards the higher reward target, but this changed as the sensorimotor costs increased (so clearly individuals were sensitive to costs and rewards, and decisions were influenced ultimately by a combination of rewards and sensorimotor costs).

Thus, the results suggest (in line with the first four experiments) that participants base their decisions on the ‘value’ of a target through a combination of its sensorimotor costs and its rewards. This is consistent with the Partially Observable Markov Decision Process model outlined in the fourth chapter. It is notable that participants did not always select the optimal target in situations where one target was clearly a better choice than another (i.e. when the rewards were equal but not the sensorimotor costs or vice versa). There are two possible explanations for this observation. One explanation is that the participants were actively engaging in exploring the task design (i.e. selecting a suboptimal target in order to better understand the task dynamics). This explanation seems unlikely given the game scenario presented (where participants were motivated to gain the highest possible score) and the fact that practice trials were provided. The alternative and more plausible explanation is that participants took too long to weight the relevant costs and rewards, and therefore defaulted to selecting one target regardless of its merits (rather than gain zero points by being timed out). This conjecture would be consistent with an ‘evidence accumulation’ model (Donkin & Brown, 2018; Huk et al., 2013; Lee & Cummins, 2004; Newell & Lee, 2011; Ratcliff & McKoon, 2008) where the system needs sufficient time for a threshold to be reached – it is plausible to suggest that on occasion there was insufficient time in this dynamical decision task and this caused suboptimal behaviours to appear (albeit relatively infrequently).

The following experiment aimed to examine the effect of age on the dynamic decision-making behaviour.

CHAPTER 8: DEVELOPMENTAL EFFECT OF DYNAMIC DECISION-MAKING (EXPERIMENT 6)

8.1 Introduction

The first five experiments involved adult humans. These experiments showed that adults are capable of combining the extrinsic rewards and sensorimotor costs associated with selecting one target over another. This raises the question of when this ability emerges in the childhood trajectory.

Childhood is a period associated with rapid cognitive and sensorimotor development (Johnson & Munakata, 2005). Work in classical decision-making tasks has shown children to be more risk seeking when two options with equal expected value are presented relative to adolescents and adults (Defoe et al., 2015; Paulsen et al., 2011). Explanations for such effects rely on the ability to mentally represent choice options along with psychology and neurobiological differences in reward sensitivity and behavioural inhibition and cognitive control (Hargreaves & Davies, 1996; Mushtaq et al., 2015; Reyna & Brainerd, 2011; Reyna et al., 2015). However, to the author's knowledge, there is no such work examining the developmental trajectory of risk-taking on sensorimotor decision tasks. To this end, we decided to explore this issue by conducting the same task as reported in Experiment 5 on a range of different aged children.

The aim of this experiment was to examine the sensorimotor decision making over different age groups. The hypothesis was that the younger children would show risky behaviour compared to the older group of age.

8.2 Methods

8.2.1 Participants

A total of 166 participants were included in this study (including the 40 adults from Experiment 5). Table 8.1 provides details about the gender and age distribution. Overall age groups, twenty one participants were left handed and 145 participants were right handed. For the 7-8 year old group seven participants were left handed and 41 participants were right handed. For the 9-10 year old group eight participants were left handed and 34 participants were right handed. For the 11-12 year old group four participants were left handed and 23 participants were right handed. For the ≥ 18 year old group two participants were left handed and 38 participants were right handed. All participants (parents/teachers for children) gave their written informed consent, children were asked and informed fully with the experiment before taking part, and the experiment complied with the ethical guidelines approved by the University of Leeds ethical committee (ethical approval number: PSC-416, date approved: 07/09/2018).

Table 8.1 Age and gender distribution of the participants in Experiment 6.

Age group	Male (n = 90)	Female (n = 76)	Total (n = 166)
7 -8	24	24	48
9 - 10	30	21	51
11 - 12	16	11	27
≥ 18	20	20	40

8.2.2 The task design

The task was the same as Experiment 5.

8.3 Results

Before conducting any inferential statistics, data were examined for violations of assumptions of normality through box- plots, Q–Q plots, histograms and Shapiro–Wilk test ($P < 0.05$), with transformations performed where necessary. A Z-score was calculated and ± 3 were assigned as a threshold to deal with outliers. A one-way ANOVA revealed that there was a significant difference between age groups in the points obtained [$F(3, 1620) = 12.59$, $p < .001$, $\eta_G^2 = 0.18$]. A post-hoc analysis using bonferroni method revealed that > 18 year old group collected more points when compared with the 7-8 and 9-10 year old group (p's < .001), however the obtained points were not significantly different between the > 18 and the 11-12 year old group. The 11-12 year olds collected more points when compared to the 7-8 year old group, but not the 9-10 year olds (p's < .7) (Figure 8.1).

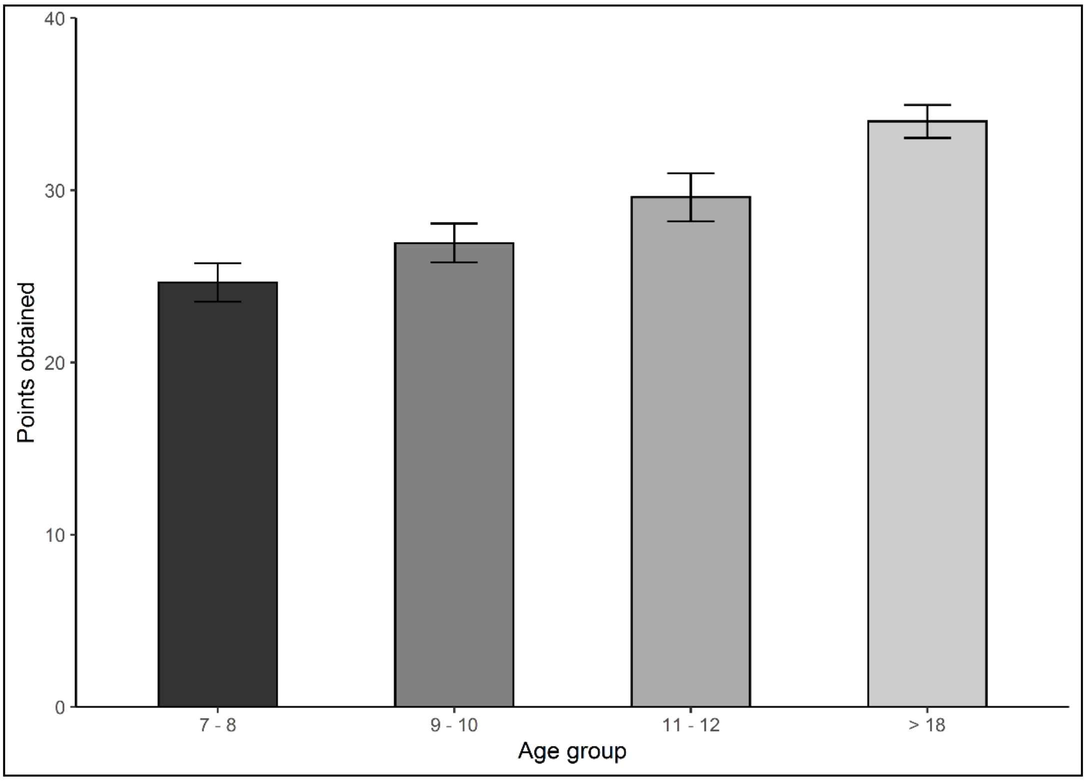

Figure 8.1 Average number of points obtained as a function of age group with standard error bars.

8.3.1 Reward advantage trial configuration

A repeated measure ANOVA showed a significant interaction between target selection and age group [$F(3, 162) = 5.73$, $p = .001$, $\eta_G^2 = 0.42$]. There was a main effect of target selection [$F(1, 162) = 333.06$, $p <.001$, $\eta_G^2 = 0.64$], and main effect of age group [$F(3, 162) = 7.28$, $p < .001$, $\eta_G^2 = 0.37$] (Figure 8.2).

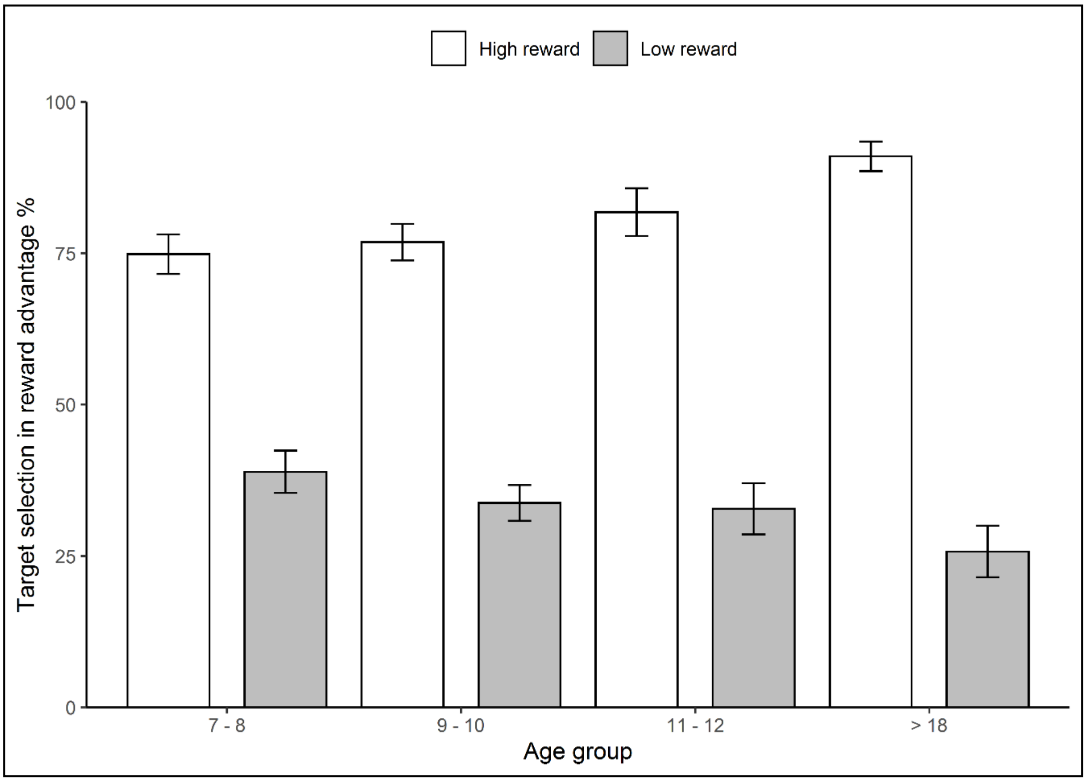

Figure 8.2 Target selection percentage in the reward advantage trial configuration as a function of age; the higher point target is unfilled bars and the lower point target is the filled bars. Error bars show standard error of the mean.

8.3.2 Distance advantage trial configuration

A repeated measure ANOVA showed no significant interaction between target selection and age group [F(3, 161) = 2.46, p = .06, η_G^2 = 0.14]. There was a main effect of target selection [F(1, 161) = 674.5, p <.001, η_G^2 = 0.47], and a main effect of age group [F(3, 161) = 2.62, p = .05, η_G^2 = 0.2] (Figure 8.3).

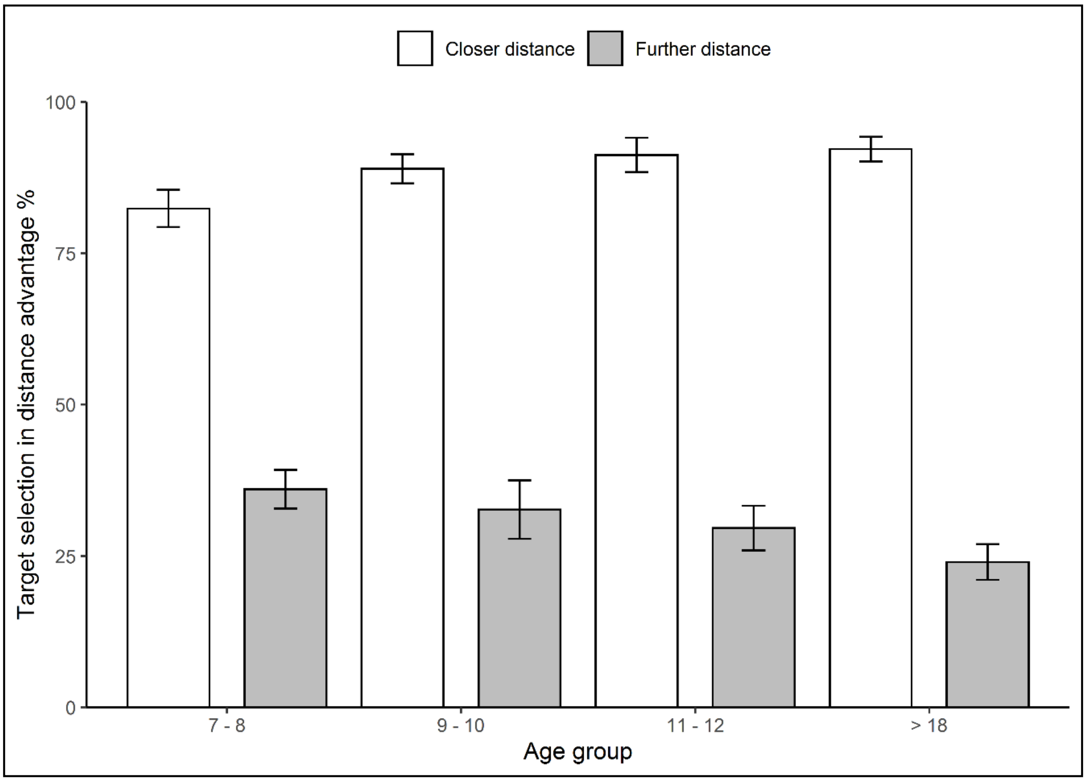

Figure 8.3 Target selection percentage in the distance advantage trial configuration as a function of age; the closer distance target is unfilled bars and the further distance target is the filled bars. Error bars show standard error of the mean.

8.3.3 Mixed trial configuration

A repeated measure ANOVA showed a significant interaction between target selection and age group [F(3, 162) = 9.03, p < .001, η_G^2 = 0. 4]. There was a main effect of target selection [F(1, 162) = 7.44, p =.007, η_G^2 = 0.25], and a main effect of age group [F(3, 162) = 6.95, p < .001, η_G^2 = 0.74] (Figure 8.4).

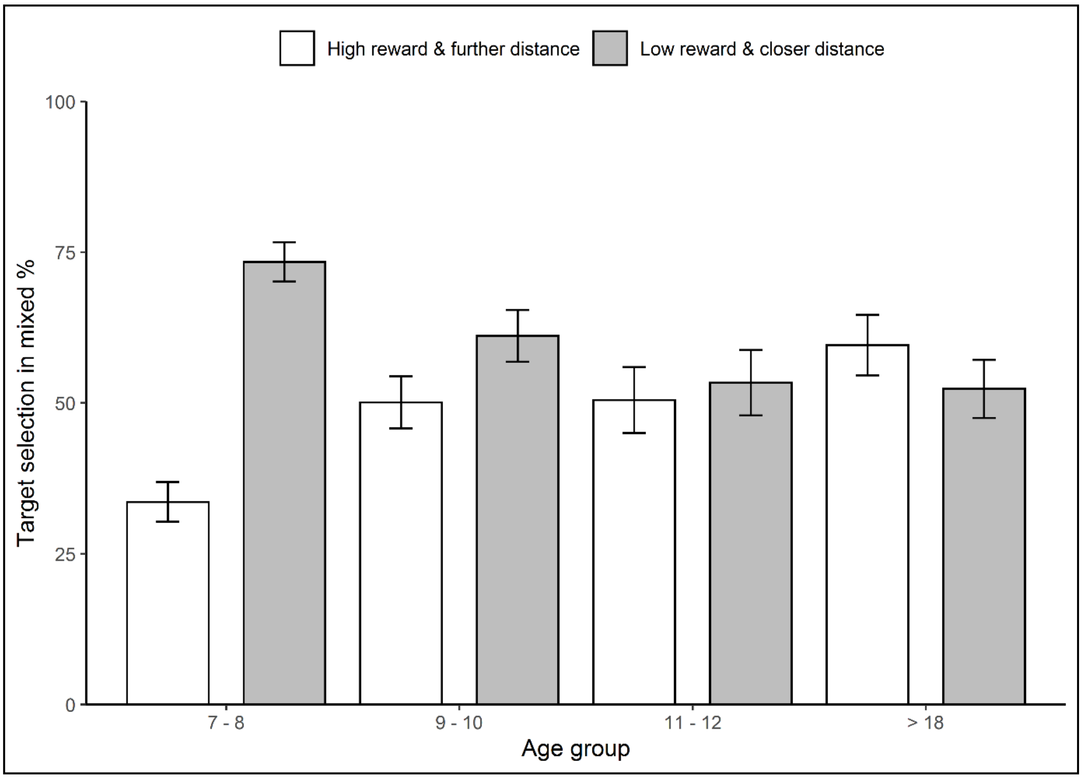

Figure 8.4 Target selection percentage in the mixed trial configuration as a function of age; filled bars showing the lower point and closer distance targets and unfilled bars are the higher point and further distance targets. Error bars show standard error of the mean.

We explored whether the magnitude of the difference between the nearer and further target had an effect on selection in the three groups of children. We found the same pattern as reported in the adults with a significant interaction between target selection and disparity size in the 7-8 year old group [$F(2, 138) = 5.08$, $p = .007$, $\eta_G^2 = 0.14$], the 9-10 year old group [$F(2, 147) = 6.74$, $p = .002$, $\eta_G^2 = 0.04$] and the 11-12 year old group [$F(2, 78) = 5.17$, $p = .008$, $\eta_G^2 = 0.24$]. There were main effects of target selection in the 7-8 and 9-10 year old group, F's < 85.1, p's < .001, however it was not significant for the 11-12 year old group [$F(1, 78) = 0.25$, $p = .61$, $\eta_G^2 = 0.001$]. There were no main effects of disparity size in the 7-8 and 9-10 year old group F's > 2.2, p's > .55, however it was significant for the 11-12 year old group [$F(2, 78) = 2.43$, $p = .09$, $\eta_G^2 = 0.04$].

8.4 Discussion

In this experiment, we examined the effect of age on decision-making when targets had different sensorimotor cost and extrinsic rewards. There were clear age effects whereby higher performance levels were found as the age group of the participants increased. However, interestingly all age groups showed adult-like behaviour with their choices biased towards targets with lower sensorimotor cost and targets with higher extrinsic rewards.

There were age differences in the biases shown across the groups such that the younger age group showed a larger bias towards selecting a target with a lower sensorimotor cost. This result makes sense in the light of the lower motor control abilities of younger children (Klingberg, 2014). It suggests, however, that even young children are tuned into their sensorimotor capabilities and use this information to choose between targets. The results also showed that it was more likely that children would select a sub-optimal target in situations where one target was clearly a better choice than another (i.e. when the rewards were equal but not the sensorimotor costs or vice versa). The most likely explanation of this finding is that the children took longer to weigh the relevant costs and rewards, and therefore defaulted to selecting one target regardless of its merits rather than gain zero points by being timed out. This provides further evidence for our suggestion that the decision-making process might involve an 'evidence accumulation' aspect where the system needs sufficient time for a threshold to be reached. It seems reasonable to suggest that the younger the child, the longer it takes to reach threshold. This would explain the observation of a higher frequency of suboptimal behaviour being observed as the age group of the group decreased.

CHAPTER 9: DISCUSSION AND CONCLUSIONS

9.1 Introduction

This thesis reports 6 experiments which involved 386 participants taking part in a novel sensorimotor decision-making task. The experimental task was designed to capture participants' behaviour towards extrinsic value (reward) and intrinsic cost (sensorimotor cost) in functionally relevant decision-making tasks (i.e. reaching for objects in the environment). Using virtual head-mounted displays, participants were presented with two targets with different reward and sensorimotor cost across experiments. The influence of reward and cost on decision-making was evident in this body of experiments and the specific pattern of results are described in the previous chapters. Here, we summarise the key findings and contributions of this work to the literature after reviewing the experimental investigation.

9.2 Review of experimental investigation

Detailed discussions have been introduced in each chapter, in this section we present the main findings and summary of each chapter. Table 9.1 presents the summary of results for the six experiments.

Table 9.1 The summary of results for each experiment.

Experiment	Summary of results
Experiment 1	• Participants were influenced by the higher intrinsic costs of the further targets. • Males were more likely to select the high reward target than females (three star manipulatin only). • Same selection frequencies were found across all manipulations (2, 3, and 5 star) despite the difference in the points available.
Experiment 2	• Participants were less likely to select the high reward target as the distance increased. • There is no effect of the motor noise manipulation.
Experimient 3	• Participants were less likely to select the high reward target as the distance increased. • There is no effect of the sensory noise manipulation.
Experiment 4	• The behaviour observed in this experiment is well predicted by a POM-DP model. • The selection behaviour changed after the repetition of the task and the gender diference noticed at the beginning disappears.
Experiment 5	• Participants biased toward the lower sensorimotor cost and the higher rewards targets. • If the sensorimotor cost is small then there was a biase towards the higher reward target. • If the sensorimotor cost increased, then there was a biase towards the closer target. • Participants were sensitive to costs and rewards.
Experiment 6	• There were an age effect on the decision making. • The older the participants the higher performance level found. • All age group showed adult-like behaviour with their choices biaed towards targets with lower sensorimotor cost and targets with higher extrinsic rewards.

Chapter two outlined the general methods used in this thesis and the piloting work that guided the development of the task. A virtual reality framework was developed to investigate human behaviour in different domains, for instance motor learning, decision making, interceptive timing, etc. This allowed for different parameters manipulation in the body of the experimental work presented in this thesis.

In chapter three of this thesis the reward and cost effect on decision making were examined. The manipulation of the target distance and reward given allowed for some understanding of the role cognitive system plays in sensorimotor decision making tasks. Increasing the extrinsic reward of the targets did not change the behaviour of participants, which further underline the importance of the sensorimotor cost (target distance) and the cognitive reward (value of the target).

In the fourth and fifth chapter, the effect of motor noise and sensory noise on the decision making task was examined. Removing the visual feedback and using the non-preferred hand of the participant did not affect participants' evaluation of the extrinsic and intrinsic value of the target. Chapter six examined the effect of task repetition over three days. The selection behaviour changed with repetition and the gender difference noticed at the beginning disappears.

Chapter seven examined the effect of dynamic manipulation of the cost and reward on decision making and found subject making optimal decisions when the cost and reward are equal, and they were biased towards the closer distance and higher reward targets. Chapter eight examined the dynamic decision making on children and found that age does not affect the riskiness behaviour and younger age showed similar behaviour as the older peers.

9.3 Overall discussion

A key contribution of this thesis comes from the novelty of the approach to tackling the topic of decision-making. Psychology has a long and illustrious history for decision-making research. Indeed, Nobel prizes have been awarded to Herbert Simon (Simon, 1979), Daniel Kahneman (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974) and more recently, Richard Thaler (Thaler, 2016) for their contributions to understanding how humans process information related to alternative choices and select actions on this basis. However, it is also notable that in all of these cases, the prizes have been awarded for contributions to the field of economics. It is clear that economic choices are an important part of the decision-making process, but it is also evident that they make up only a tiny fraction of the types of decisions humans make hundreds of times a day and billions of times across a lifespan. These choices invariably involve the sensorimotor system - for choice selection to be implemented and have impact on the world around us, it necessitates action execution. Yet, investigations into the influence of this component of decision-making has largely been neglected. Indeed, almost the entirety of psychological sciences investigations into the topic have involved experimental designs that either minimise the involvement of the sensorimotor system (relegating action execution element to the press of a button on a stimulus response pad) or make sensorimotor errors an impossibility or rare exception (to be excluded from analysis) in their research designs.

In the mid-2000s, predicated on this body knowledge and clear gap, a new area of research on “sensorimotor decision-making” emerged (Trommershauser et al., 2003a, 2008, 2005, 2011, 2003b). Yet, the majority of this work has involved adapting principles from cognitive decision-making under risk and modelling responses from simple sensorimotor decision tasks with little to no cognitive demands (see for example Trommershauser et al., (2008)) in an analogous fashion.

The experimental design employed in this thesis takes a different approach to these two bodies of work. Instead of relegating sensorimotor execution to bit-part player, or stripping sensorimotor choice of any reasonable cognitive demands, the experiments presented in this thesis involve integrating the two. This intersection is where a large proportion of real-world decisions reside. Take for example the everyday case of reaching for a cereal box at the back of top shelf of the supermarket. Not only does a decision maker have to factor in the expected reward of achieving the goal, but one must also consider the sensorimotor costs of carrying out the action. In some cases, this might result in asking for help from a taller shopper passing by. It is this integration into decision-making that has finally started to gain traction (Green et al., 2010; McDougle et al., 2016, 2019; Parvin et al., 2018) and this thesis adds to this nascent body of work.

A related benefit to this sensorimotor - cognition approach to decision-making are potential contributions that this type of approach could have in the future in applied settings. As a Paediatric physiotherapist, my motivations for carrying out this thesis were focussed on the limitations of extant approaches to assessing children’s movements in the clinic (Graham et al., 2004; Henderson et al., 2007; Russell et al., 2004). Many cases involve rudimentary tasks and subjective clinical judgements. My experiences have taught me that many children with underlying difficulties can effectively carry out tasks in a clinical setting, but such assessments do not accurately capture the difficulties they face outside of the clinic and in the home or school (Faught et al., 2008; Rosenblum, 2006; Tieman et al., 2004). Here, not only does a child have to be able to execute an action whilst maintaining postural stability and/or execute a fine motor control task without dropping an object, they might also be holding in their working memory a myriad of related and unrelated tasks that they must carry out (which some may in some cases be immediately pressing - e.g. pick up object A to carry out Action B). It is these types of challenges that are not well captured in physiotherapist practice but where the types of tasks employed in this thesis might be able to gain some traction.

It is also worth speaking to the experimental environment that the tasks in this thesis were performed in. The potential for virtual reality technology in psychological research has long been recognised (Loomis et al., 1999; Wann & Mon-Williams, 1996) and its use in psychology is becoming more mainstream, however, the dominant methodology for studying decision-making involves traditional 2D technology and a keyboard and mouse (or a stimulus response pad) for interaction. In traditional sensorimotor control laboratories, these methods may be extended to sensor based tracking and bespoke objects. However, it was clear from an early stage in this thesis that the novel experiments reported in this thesis would have been impractical to impossible to carry out in such a setting. Thus, in collaboration with colleagues with expertise in VR task programming (which has since been formalised as a series of tools known collectively as the Unity Experiment Framework [UXF; (Brookes et al., 2019)], we developed this experimental task- which provided a level of scalability and adaptability that allowed me to collect data on a large number of participants (total of 386 participants in the reported experiments alongside 503 participants involved in the preceding period of several iterations of piloting and refining the task design).

It is clear that as the cost associated with these devices continues to reduce and computational power increases, which this type of approach will start to become ubiquitous in this field. Data collected from the baseline assessments described in this thesis provided a proof of concept for a recent methods behaviour advocating for behavioural sciences to take advantage of the power of VR and the UXF library (Brookes et al., 2019). The work presented here provides a canonical example of the value of VR for examining the processes underlying cognitive and sensorimotor processes. The tasks employed in this thesis will be made available to the research community to help in supporting more researchers to make the leap over to VR for psychological sciences research.

9.4 Limitations and future work

There are several limitations in this thesis that could be overcome in the future research. These are described below:

1. An experiment with no time-out in the decision making session might help us to understandthe relationship between the cost and reward in more details. For example, participants might feel there is enough time for them to carry on the movement endlessly to hit the target.
2. Due to time restrictions, recruiting children in experiment one to compare their decision making behaviour with adult data presented would strengthening our understanding of the developmental differences in the decision making processes captured in the task.

3. Experiment four sample size is relatively limited compared to other experiments presented because it was difficult to recruit participants willing to come twice a day for three consecutive days. Thus the sample was limited only to 20 participants. Moreover, the sample size in experiment six is not equally distributed across different age groups, which might have some implications on the observed results.
4. An advantage of using a virtual reality systems is portability and accessibility, however changing the experimental settings (i.e. laboratory setting and museum settings) might have some effect on the results observed. Experiments one to four carried out at a laboratory setting and experiments five and six were carried out in both settings (i.e. laboratory and museums).
5. Due to time restrictions, some of the analysis was not carried out. For instance the movement trajectories data were not investigated carefully in the presented thesis. Further investigation and deeper look into the rest of the data available under our hands would shed more light into the movement trajectories behaviour in decision making using virtual environment.
6. There were no effect of noise in experiment two and three (motor and sensory noise). One explanation could be that the level of noise presented was not enough, and a stronger source of noise could lead to another observation.
7. The same control group was used in experiment two and three, which might affect our results.

9.5 Concluding remarks

The work presented in this thesis support the idea that decision making processes are complex and there are different underlying mechanisms involved. The balance between extrinsic reward and intrinsic cost of a specific target are examined in the data presented. Both of these features might be important in making optimal decisions especially in virtual environment. The results might help understand how the interaction between motor and cognitive functioning influence decision making. Using virtual reality in this thesis might open new windows on the use of immersive technologies in understanding human behaviour.

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