EXPERIMENTAL INVESTIGATIONS ON RISK TAKING IN SENSORIMOTOR DECISION MAKING

by

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Bu tezi, hayati dolu dolu yaşayan ve zorluklar karşısında asla pes etmeyen, sevgili anneme ithaf ediyorum.

I dedicate this thesis to my beloved mum who lives life to the full and never gives up despite any difficulties that arise in the life.

INTELLECTUAL PROPERTY AND PUBLICATIONS

The candidate confirms that the work submitted is her 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.

Poster presentation of the experiments reported in Chapter 2 and Chapter 3:

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ABSTRACT

It has long been known that humans display a number of cognitive biases when they are asked to select from a series of possible choice alternatives in economic decision-making tasks. In stark contrast however, the last two decades of research on sensorimotor control have shown that humans are able to exhibit statistically optimal behaviours (i.e. select the most appropriate action from a repertoire of options) when they act on the environment. Given that many critical decisions in the real world require not only selection but also action, it is surprising that there has been little crosstalk between these areas of research. This thesis bridges this gap in the literature by introducing a new experimental framework that allows the manipulation of features related to action selection and execution to understand how these processes interact to manifest in decision-making. Specifically, a novel multi-trial decision-making task is developed where participants are asked to select from a series of options with varying levels of risk and reward (equivalent to choice selection in economic decision-making) and implement their choices with actions that place demands on the sensorimotor system. One particularly prevalent bias in the decision-making literature is risk aversion under uncertainty, but recent studies have shown that this phenomenon can be reversed when the task is reframed as a sensorimotor reaching task. This thesis examines this bias in detail by experimentally manipulating key component parts in choice selection and action execution. There is a particular focus on the role of agency, feedback (either veridical or predetermined), motor competence and learning. Visual execution error has consistenly resulted in riskier behaviour as well as better error correction. Together, this work demonstrates the interplay between cognitive and sensorimotor systems in choice selection by illustrating the bilateral relationship between parameters driving action selection and execution interact to produce decision-making.

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Chapter 1 General Introduction

1.1 Research on Decision-Making

Decisions are the building blocks of life. Given the frequency with which we all make decisions and thus, the intuitive familiarity we have with the process of decision-making, it is no surprise that this topic has been the focus of intense research for over 100 years. Indeed, the psychological examination of decision-making behaviour has resulted in three Nobel prize winning research programmes (Kahneman & Tversky, 1979; Simon, 1955; Thaler, 2000). Yet, at the same time, given how diverse decisions can be- ranging from the very mundane (e.g. should I take the motorway or the backroads to work today?) to the life-changing (e.g. should I move to a different country to undertake doctoral training?), it is no surprise then, that many parts of our understanding of the mechanisms underlying decision-making remain incomplete.

At its most fundamental level, we can think of separating decision-making into two component parts: (i) making a choice, and then (ii) acting upon that choice (Rasmussen, 1993). In the scientific literature, we refer to an action *selection* component – a process that involves value processing and determines which choice must or should be made (e.g. "I need to go and get some milk from the shop") and a second action *execution* component that implements the selected choice and interacts with the world around us (e.g. the physical act of going to the shop to get milk; Orasanu & Conolly, 1993).

The majority of research on the psychology of decision-making has been inspired by an economic perspective. The aforementioned Nobel prizes were awarded for their psychological contributions to economics (and ultimately have resulted in the creation of a whole new discipline of behavioural economics). These types of research programmes ask questions that probe the factors that influence choice *selection* (Hensher & Johnson, 2018; Newell, Lagnado, & Shanks, 2015; Shafto & Bonawitzx, 2015). In keeping with our earlier example, why choose to go for milk over orange juice? What brand of milk might you purchase? Does your appetite for a particular choice change as a function of experiencing that choice? What about the impact of previously experienced “rewards” for choosing an alternative? The questions are myriad, but a common feature of all of this type of questioning is that the key neural architecture responsible for making these decisions is principally housed in the prefrontal cortex and the domain of “higher order” cognition (Evans, 2008; Lieberman, Gaunt, Gilbert, & Trope, 2002; Phillips, Fletcher, Marks, & Hine, 2016).

Imagine now that you did indeed follow through with your decision to go to the shop and buy a bottle of milk. You arrive home and desire to make a cup of tea. A series of decisions need to be implemented to achieve this goal. Yet, we do not muse over the possible trajectories that one could take to reach towards the milk bottle and then select the optimal one (Wolpert, 1997), nor are we explicitly aware of the amount of force needed to apply with our hands to ensure the bottle does not slip through (Seidler & Stelmach, 1995; Wolpert, 1997). The processes involved in making these types of decisions and enacting upon them has principally been the domain of sensorimotor learning research (Held & Freedman, 1963; Shadmehr, Smith, & Krakauer, 2010; Wolpert, 1997). These types of questions have often focussed, explicitly or implicitly, on the role of the sensorimotor system - a network of neural structures which include all the afferent and efferent connections and the central architecture involved in integrating information and processing to produce movement (Riemann & Lephart, 2002). The cerebellum and basal ganglia are thought to be the key players here in the modulation and regulation of sensorimotor commands (Ghez, 1991; Riemann & Lephart, 2002) - and thus, the focus has almost exclusively been on the action execution elements of decision-making. While historically, many have refrained from labelling such investigations as decision-making per se, a number of prominent researchers have started to emphasise the need for motor execution to be understood as decision-making (Wolpert & Landy, 2012).

Given the obvious relationship between these component parts, it is striking to note that research into these two broad areas has largely developed independently, with little overlap or cross referencing to one another. In short, historically, researchers have either examined the cognitive processes involved in action selection or the sensorimotor processes that produce action execution.

1.2 An Alternative Take on Choice Selection

There has been a growing recognition of the symbiotic relationship between sensorimotor and cognitive systems. At its broadest level, and a hypothesis that ventures into the realms of philosophy, has been the theory of embodied cognition. This is the idea that cognition is a product of a symbiotic relationship between brain body and environment (Lakoff & Johnson, 1980). In line with this world view, and more specific to decision-making, are emerging reports demonstrating pathways between the cerebellum and areas implicated in higher order selection (Blakemore, Frith, & Wolpert, 2001; Imamizu & Kawato, 2009), which present a neuroanatomical gateway for interactions between cognitive and sensorimotor systems to manifest.

Predicated on these ideas that higher order cognition and the sensorimotor system may be more closely intertwined than previous investigations have indicated (Wilson, 2002), this thesis sets out to bridge a highly pertinent gap in the field and sets the scene for a new perspective on decision-making. This thesis considers action selection and execution as more equal players in behaviour than previous work has implicitly acknowledged. Specifically, the work reported in this thesis involves developing a new experimental framework that allows the manipulation of features related to action selection and execution to understand how these features interact to manifest in decision-making.

Given that this work falls at the intersection of sensorimotor control and behavioural economics, this general introduction chapter will refrain from providing a historical overview of each independent area and their most influential theories; these subject matters are too vast to do justice in one single thesis. Instead, the following sections present a few select core concepts that are most relevant to the integration of choice selection with action execution. The introduction also covers some descriptions of key studies that have helped shape this nascent area and we will refer to these ideas throughout the thesis as they relate to the experiments reported in subsequent chapters.

1.2.1 A Brief Overview of Economic Choice Selection

Any examination of decision-making must, as a matter of course, consider Expected Value, Expected Utility Theory (Von Neumann & Morgenstern, 1944) and Prospect Theory (Kahneman & Tversky, 1979).

Expected Utility is now often presented as a highly critiqued model of how humans make choices. In short, it proposes that when presented with options, an agent will calculate the probability and magnitude and a multiplication of these variables will lead to “expected value”, or EV, of the choice; and rational choice selection is then simply the process of selecting the option that yields the highest EV (Christopoulos, Tobler, Bossaerts, Dolan, & Schultz, 2009; Devlin, 2008).

Seminal evidence subsequently emerged showing that individuals often violate these assumptions of EV and thus, deviate from rationality. Take for example, a situation where you must choose between two different lotteries: in one option, buying a ticket is known to result in a 50% chance of winning £3000; whilst a second option guarantees the award of £1000. The first option has the higher expected value (E = p.X; 1500, 1000, respectively), but it is a matter of empirical observation that the vast majority of people presented with the type of scenario posed here would prefer the second option and take the sure-fire £1000.

It is also the case that when posed with these scenarios, context is an important factor. For example, risk appetite may vary as a function of current wealth. The options considered above may be quite different if one already has a few million pounds in the bank. This is the fundamental basis of Expected Utility Theory (EU), formed by Neumann & Morgenstern (1947). Whilst EV might be thought of as an objective value of outcomes, EU considers the role of subjective evaluation of outcomes and seems to better fit the economic decisions of individuals (Schultz et al., 2008).

Prospect theory (Kahneman, Slovic, & Tversky, 1974) emphasises the importance of two variables in decision making. First, it proposes that ‘losses loom larger than gains’- that is, people are prone to overweighting the influence of a potential loss relative to the equivalent expected reward (see Figure 1.1A). The second is that people will systematically underweight both high probability and low probability events (see Figure 1.1B).

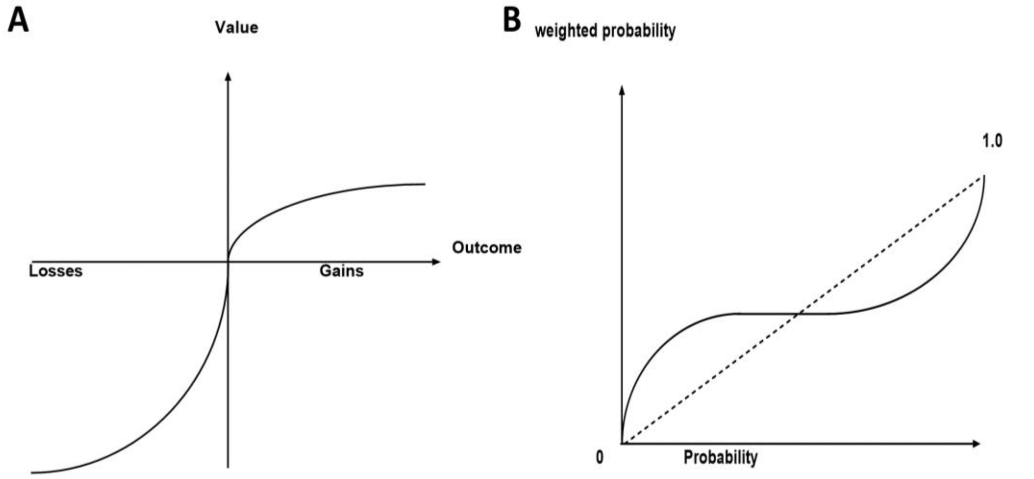

Figure 1.1 Value and Probabilities According to Prospect Theory (A) When people lose, the value is over-emphasised compared to gains. When people gain, the value is actually diminished by more gain. (B) People appear to round up probabilities close to both 1 and 0 and as a result, over-estimate small probabilities and underestimate large probabilities e.g. an event with 80% probability may be treated much lower.

Following Knight (1921), there has been a key distinction in the decision-making literature between action selection that takes place "under risk" and action selection that takes place "under uncertainty". In the former, potential consequences (both advantageous and disadvantageous elements) of the different options are known by the decision-making agent. An example of risk is rolling a pair of dice. The odds are known for each possible outcome (provided that the dice are fair) before rolling.

In contrast, decision-making under uncertainty has ambiguous or unknown outcomes. The two decision-making contexts are marked by different choice profiles (Brand, Labudda, & Markowitsch, 2006) with a plethora of empirical studies showing people are more willing to gamble under risk, where the probabilities are known, in comparison to uncertainty (Camerer & Weber, 1992; Ellsberg, 1961; Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005).

A famous example to illustrate these differences is the Ellsberg paradox. Imagine a situation where there are two decks which each contain 20 cards. One of the decks comprises 10 yellow and 10 green cards (a “risky” deck) and the second deck has 20 yellow or green cards where the composition of yellow and green cards are unknown (an “uncertainty” deck). The game requires a bet on a colour. If the drawn card is the chosen colour, a player will win a fixed amount and nothing otherwise. In these types of environments, people seem to prefer to gamble on picking a yellow card from the risky deck rather than the uncertain deck and gambling on green follows the same trend.

In theory, the *subjective* probability of yellow in the uncertain deck is seen to be lower than the *subjective* probability of yellow in the risky deck and same trend for green; however, the probabilities of yellow and green from the uncertain deck must equal 1. This is the root of the paradox (Camerer & Weber, 1992; Ellsberg, 1961; Hsu et al., 2005), and highlights the importance that the absence of information can play on choice selection (Fox & Tversky, 1995; Frisch & Baron, 1988).

Uncertainty and risk have also shown to have distinct neural correlates (Brand, Recknor, Grabenhorst, & Bechara, 2007). In decision making under uncertainty activation in the orbitofrontal cortex is heightened- a structure which is central to the perception of reward and punishment feedback, including anticipation and receipt of feedback. Alongside this, the amygdala also exhibits heightened activity- the amygdala responds to the motivational value of incoming information and the processing of a “vigilance”/ evaluation system (Clark & Manes, 2004; Hsu et al., 2005; Mushtaq, Bland, & Schaefer, 2011; Rolls, 2000; Uytun, 2018), In contrast, decision-making under risk seems to relate to the dorsolateral part of the prefrontal cortex which is primarily implicated in cognitive processing e.g. feedback evaluation and working memory (Brand et al., 2006; Clark & Manes, 2004; Hsu et al., 2005; Rowe, Toni, Josephs, Frackowiak, & Passingham, 2000).

1.2.2 Sensorimotor Decision-making

At the turn of the 21st Century, a group of researchers based primarily in New York University set about examining whether the types of decision-making biases illustrated by prospect theory might also manifest in the sensorimotor system (Trommershäuser, Maloney, & Landy, 2008). Their approach was to take classic economic choice tasks and provide analogues for the sensorimotor system. The most fundamental form of this task presents participants with two circles intersected on a computer screen (Figure 1.2). One of the circles is a "reward" circle, where the magnitude of reward increases from the edge to the centre. The other circle is a "penalty" circle. Participants are asked to collect as many points as they can by tapping the reward circle (under time constraints) and understand that the closer to the middle of the circle they are, the more points they gain. They must however trade this potential reward off with the possibility that as they aim for the middle of the target, they stand more chance of erroneously hitting the overlapping penalty circle and risk losing points. By changing the degree of overlap, risk and reward can be manipulated in a mathematically equivalent way to asking participants to select options in classic cognitive economic choice tasks.

A decade-long programme of research using this type of motor decision-making task (Gepshtein, Seydell, & Trommershäuser, 2007; Neyedli & Welsh, 2013, 2014, 2015; Trommershäuser, Gepshtein, Maloney, Landy, & Banks, 2005; Trommershäuser, Landy, & Maloney, 2006; Trommershäuser, Maloney, & Landy, 2003b, 2003a; Trommershäuser et al., 2008), gave rise to the idea that the processes governing sensorimotor decision-making were in stark contrast those governing the cognitive decision-making: They were "optimal" and devoid of the biases that are so obviously apparent in cognitive decision-making and thus not well explained by prospect theory.

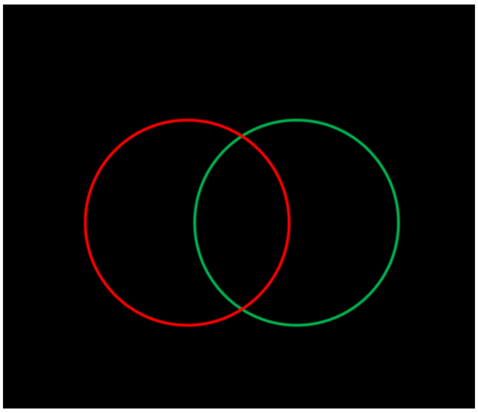

Figure 1.2 A Sensorimotor Decision Making Under Risk Task. Participants are asked to tap anywhere in a green circle on a computer screen on within a time restriction. The green circle is the reward circle. Tapping anywhere on the screen corresponds to a lottery but the centre has more reward than the edge of the green circle. The red circle is the punishment circle where participants lose point by tapping. There are numerous versions of this task where the location of the circles, the distance of between circles and time constraints of execution (tapping) have been manipulated. This figure is reproduced based on Trommershäuser et al. (2008).

The researchers came to this conclusion following their application of Bayesian Decision Theory to their data. Bayesian Decision Theory (Savage, 1954; known as founder of modern Bayesian decision theory), as the name indicates, is rooted in Bayes Theorem – a centuries old formula that has only recently had the commensurate computational power required for it to be feasibly implemented in real-world situations (Edwards, Lindman, & Savage, 1963).

Bayes theorem deals with making inferences about the probability of an event given another event- i.e. it deals with conditional probabilities (see Equation 1):

Equation 1 $$P(A|B) = \frac{P(B|A).\ P(A)}{P(B)}$$

Conditional probabilities have three components and can be explained with the following example; you are at work and suddenly feel restless. Your friend at work was sick with flu last week. Does it mean that you have flu, too? You sneeze and have a fever and you know that people with flu sneeze and have a fever 90% of the time. You turn to google and learn that only 5% of population will catch the flu in the current year and that 20% population in the current year sneeze and have a fever. What do you think the probability of you having flu is, given these symptoms?

Bayes theorem helps us update our hypothesis based on new observations. Your hypothesis is that you have the flu and your observation is that you have the symptoms. You have two additional pieces of information that would help you more precisely estimate the probability of having the flu given your symptoms.

When you use Equation 1, P(A) is the probability of you having flu (0.05), which is referred to as the prior probability; P(B|A) is the probability of symptoms given that you have flu (0.9), known as the observation; and P(B) is the probability of you having the symptoms (0.2), which is referred to as the likelihood probability.

Now using the equation, you can calculate the posterior probability of you having flu given that you have the symptoms (0.225). Using Bayes theorem, the posterior probability ($P(A|B)$) can be estimated by using the conditional probability ($P(B|A)$), prior probability ($P(A)$) and likelihood probability of the event ($P(B)$).

Bayesian decision theory extends this approach and includes a Maximisation Expected Gain (MEG) parameter (Trommershäuser et al., 2003a) (see Equation 2):

Equation 2 $$\Gamma(\mathrm{S}) = \sum_{i=0}^{N} G_i P(R|S) + G_{timeout} P(timeout|S) + \lambda B\,(S)$$

Here, $\Gamma(\mathrm{S})$ stands for expected gain through making a decision which is a sum of gain ($G_i, G_{timeout}$) from two possible outcomes according to their probabilities ($P(R|S)$ and$P(timeout|S)$), and the biomechanical cost $(\lambda B(S))$ required by each movement. The possibilities are calculated following Bayes Rule (Equation 1).

Through the implementation of Bayesian Decision theory, these researchers were able to calculate the optimal behaviours to maximize gain and minimise losses and empirically observed that tasks framed as sensorimotor in nature showed participants could maximise expected gain and minimise expected loss.

According to Bayesian theory, when the distribution of prior probabilities is weak or uninformative, posterior probabilities will be more heavily driven by observations, whereas, strong prior probabilities will drive estimations of posteriors (Edwards et al., 1963). Importantly, the priors are updated as events occur; therefore, it is fair to say that every former posterior will give rise to a stronger estimation of prior probability for the next estimation (Edwards et al., 1963). If one event (outcome or set of outcomes) is experienced more than another event, the posterior probabilities of the first event will be stronger (Steyvers, Lee, & Wagenmakers, 2009).

1.2.3 Agency and Decision-making

What is the purpose of decision making? Whether we come from a sensorimotor or cognitive perspective to this question, at its most fundamental level, we make decisions in order to act on and change the environment around us. It is this ability to be able to act that gives us agency (Bandura, 1982; Friston et al., 2013; Gallagher, 2000; Haggard & Chambon, 2012a).

Whilst the topic of agency has often transitioned into the domains of philosophy and law, in psychology, in psychological experiments agency has often been operationalised through initiating or triggering an action (Haggard, 2017) and closely related to action preparation driven by the primary motor cortex (Passingham & Wise, 2012).

Researchers often make a distinction between the three component parts of the agency construct: there is: (i) the feeling of agency; (ii) the judgement of agency; and (iii) the ownership of agency (Synofzik, Vosgerau, & Newen, 2008). The feeling of agency relates to the experiential feeling of being the agent, whilst judgment of agency relates to the experience of being the agent (e.g. feeling of ownership) (Jeunet, N'Kaoua, & Lotte, 2016; Synofzik et al., 2008). The feeling of agency can be considered independent from any verbalisation; rather it is supposed to be based on the signals from action execution, whereas, judgment of agency is when an individual has to judge whether a movement is their own (David, Stenzel, Schneider, & Engel, 2011; Farrer & Frith, 2002). Finally, an ownership of agency relates to the ability to be able to accurately classify whether one's own body is moving (whether under voluntary or involuntary control) (Haggard, 2017; Synofzik et al., 2008).

There are primarily two ways of measuring sense of agency in the literature: explicit and implicit approaches. Explicit approaches involve asking an individual if they are in control of what they are doing (Haggard, 2017). Even though this measure seems direct and quite straightforward, there are a number of reported limitations to measuring sense of agency in this manner. Human biases in outcome evaluation and inference on causality lead to the assignment of agency to unrelated events (Wegner & Wheatley, 1999). For example, people report that they are in control of an outcome, when they successfully predict a chance outcome (Langer & Roth, 1975) and these biases are even stronger in situations regarding positive outcomes (Bandura, 1982). An example of this is a study where participants are asked to direct a moving dot by pressing keys on a keyboard. Participants are required to move the dot from one point to another. In one condition participants are in control of the movement of the dot and in the other, the task is designed to omit the erroneous commands of participants while moving the dot. Then the participants report how much control they have had on moving the dot after each trial by using 9-point scale; they reported higher sense of agency on positive outcomes when in actual fact the erroneous comment was ignored. In other words, participants' sense of agency escalates with positive outcomes and better execution feedback (Wen, Yamashita, & Asama, 2015).

An implicit approach to measuring is more likely to reflect the lived everyday experience of agency- for we do not often have third parties asking us about our role in the causation of an event in any explicit way (Haggard, 2017; Synofzik et al., 2008). The implicit measures are interval of action-outcome (intentional binding) as well as actual degree of control (Berberian, Sarrazin, Le Blaye, & Haggard, 2012; Haggard, 2017). Intentional binding is described as the perception of the interval between a voluntary action and an outcome, which is shorter than the perception of the interval between similar involuntary movement and same outcome event (Berberian et al., 2012; Haggard, Clark, & Kalogeras, 2002).

Rather surprising are analyses showing little correlation between explicit and implicit measurements of agency (Dewey & Knoblich, 2014; Haggard, 2017) suggesting that they tap into fundamentally different component parts of the construct of agency. There is now a growing consensus that if one wants to tap into the feeling of agency, then this should be measured implicitly to avoid contamination from biases arising from the *judgement* of agency (Dewey & Knoblich, 2014).

1.2.3.1 Manipulating Agency

Key to investigations into the underlying nature of agency are manipulations of the construct through experimental tasks. The classic approach in experimental psychology to dissociate agency comes from asking participants to carry out actions on a computer versus showing the participant a computer carrying out the same task without any input from the user.

One notable and elaborate manipulation of this type comes from Berberian and colleagues (2012). These researchers asked participants to complete a simulated task mimicking the role of an air traffic controller, in which they needed to safely navigate an aircraft through a flight path and provide real-time solutions to any problems that might arise over the course of the flight. Each trial involved a sequence of 5 steps.

Shortly after the start of a trial in which participants were supervising a flight, a conflict (in the form of another aircraft in the path) emerged. At this point, the participants had to indicate that they had detected the conflict by applying a red circle around the intruding aircraft. Following this, a course of action had to be determined (the action selection phase- how should I best divert the aircraft away from the supervised flight path?). Subsequently, the participant needed to implement the decision through the use of a scroll wheel, indicating a new trajectory for the intruding aircraft (an action implementation phase) and finally, participants executed the implemented decision by pressing an engagement button. After a controlled temporal delay, feedback relating to the success of the action engaged was provided to participants indicating whether the problem had been successfully resolved or not.

Crucially, this separation of the phases of action selection, implementation and execution allowed the researchers to systematically vary the amount of control a participant had over the task. In every different block, one of these steps was taken away and implemented by a computer. At the end of every trial, participants were asked to report their estimates of the temporal delay between the action and the result (Figure 1.3) as well as the subjective report of how much they felt in control while navigating the aircraft after each block. This study provided some evidence that action outcome interval was strongly related to the subjective report of level of sense of agency which was dependent on actual action-effect interval.

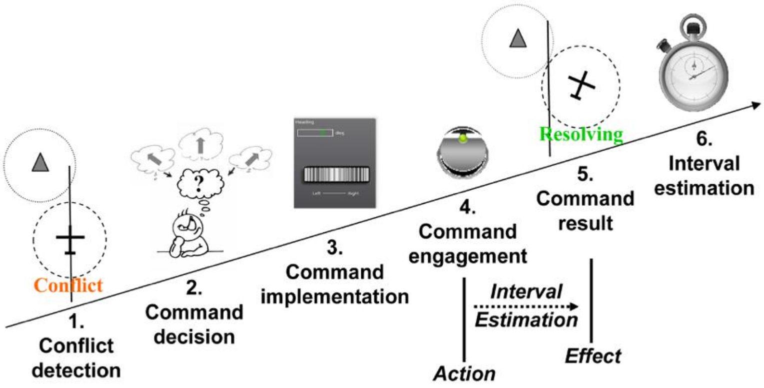

Figure 1.3 Experimental task examining agency. The task requires the participants to supervise a flight in which they face a conflict, being thatanother aircraft is in their path. Participants must indicate the conflict by applying a red circle around incoming conflicting aircraft. Subsequently, partcipants must decide a course of action to divert the conflicting aircraft away from the supervised flight path (action selection). Then, participants implemented the decision using a scroll wheel, indicating a new trajectory for the aircraft leading the conflict (action implementation). Lastly, participants were required to press the engagement button to execute the implemented decision. After a controlled temporal delay, participants received feedback as to whether the conflict is resolved. Then participants are required to estimate the internal delay. Image appears courtesy of Berberian et al. (2012).

In another recent study manipulating sense of agency, the experimenters gave participants in different groups different sets of information to manipulate their belief about the causal relationship between action and outcome (Parvin, McDougle, Taylor, & Ivry, 2018). Participants performed a reaching task to one of two targets by performing a shooting movement towards the selected target (Figure 1.4).

One group of participants (a “sense of agency” group) was told that trial outcome (win/loss) was related to the accuracy of their reaches towards a target. A second group was told that the outcome was related only to the selected target and its reward properties.

In reality the two targets had an equivalent expected value- which was achieved by predetermining reward schedule and the probability of hit and thus the outcomes for both groups were the same, whether or not participants were told they were in control. The expected value of targets in individual trials differed throughout the experiment.

Importantly, while participants movement towards the target there was no online visual feedback (Figure 1.4). This lack of feedback while executing shooting was important because it could influence the sense of agency in two ways: (1) Instant visual feedback of trajectory might generate a belief of sense of agency in the condition where participants were told that they were not in control (Farrer et al., 2008; Moore & Haggard, 2008; Schlaghecken & Eimer, 2004); and (2) Since the success probabilities were predetermined, participants were either given veridical feedback or false feedback and to avoid mismatch between proprioceptive signals and visual information, it was important to blind participants to their online movements.

Selecting a target with lower hit probability and higher reward was defined as risky; participants' choice biases was calculated the ratio of the amount of risky target over the total number of trials. The results showed that participants in the agency group exhibited more risk seeking than the group who did not have information about agency, even though the outcomes were equivalent across both conditions (Parvin et al., 2018).

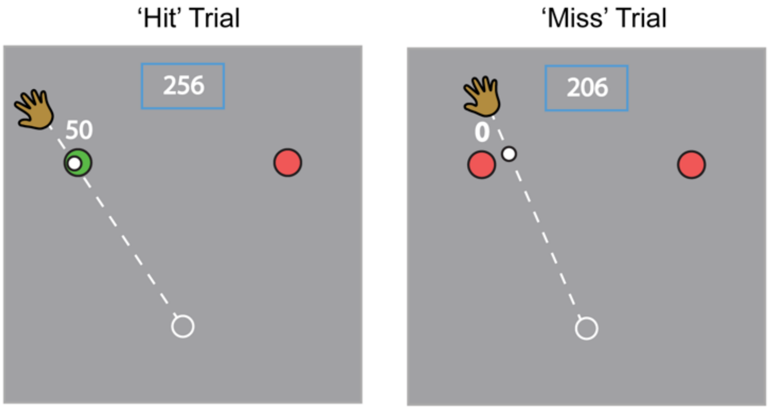

Figure 1.4 A Sensorimotor Agency Task. In one group, subjects were told that they do not have any control of the consequences of the choices: that the outcome is pre-programmed. In the latter group, participants were told that they were in control. This manipulated the sense of agency. Participants required to shoot the target to select. There are two possible outcomes: hit and miss. Hit outcome is when the endpoint of the participants' endpoint falls within the targeted circle. Miss outcome is when the endpoint of the participants' endpoint falls out of the targeted circle. Image appears courtesy of Parvin et al., (2018).

As the two experiments presented above have illustrated, the manipulation of agency can have a profound impact on one's decision-making strategy. Related work has examined whether choice behaviour deviates from optimality when agency is manipulated. As described earlier, work applying Bayesian decision theory on sensorimotor decision making tasks has shown behaviour to be close to optimal, but this is not always the case (Green, Benson, Kersten, & Schrater, 2010; Ma, 2019; Sanborn & Chater, 2016; Wu, Delgado, & Maloney, 2009). Indeed, the degree of control one is able to exert on the environment and prior information can have a profound impact on this deviation. Variation in, or deviation from, optimality seems to be related to knowing prior probabilities and conditional probabilities accurately (Green et al., 2010; Ma, 2019) or not knowing them at all (Sanborn & Chater, 2016). To illustrate, we consider one of the most influential examples from the literature next.

Green et al., (2010) investigated whether people make optimal decisions when they are in control of the environment compared to when the computer controls the environment in a probability matching task. The task they used involved a roulette wheel consisting of pieces in two alternating colours on top of which an arm would spin (see Figure 1.5). To win, participants were asked to decide which colour the arm would stop on.

The experimenters employed two manipulations. In one, the sense of agency was manipulated with either the computer or the participants stopping the arm from spinning. Participants thought they were in control of stopping the arm; however, the termination was determined by the computer. In the second manipulation, the accuracy of the representations of the visual information and corresponding probabilities manipulated. The roulette wheel was divided into either equal or unequal pieces. However, in both cases the visual appearance of equal division did not accurately reflect the probability of what colour the arm would stop on, as the results were predetermined. Whilst visually it appears there is an equal probability of the arm landing on a particular coloured piece, the participant's experience should inform them that this is not the case and they should adapt a different betting strategy.

The result showed that participants chose a piece’s colour with high probability of win when they thought they were in control and the pieces showed an accurate representation of the probability of winning. Interestingly, when there was a visually inaccurate representation of landing on the equal pieces and when they thought they were not in control, they were more likely to make suboptimal decisions- despite the outcomes being the same across all conditions.

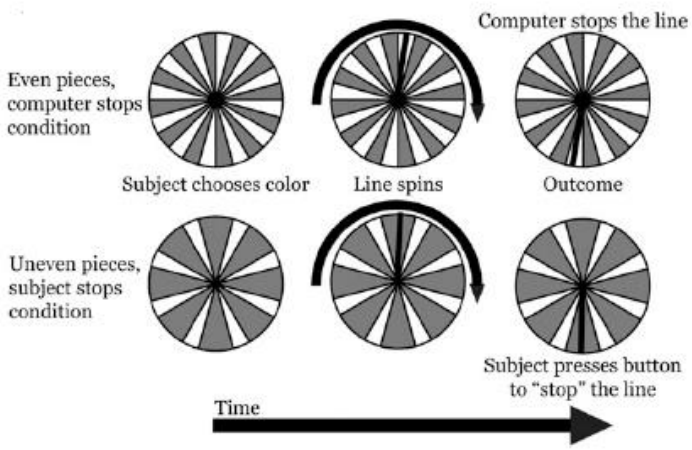

Figure 1.5 Agency in a probability matching task. A roulette game where a computer determines where the roulette arm terminates. Even though the computer stops the arm in all conditions, the participants believe they are in control of the termination of the arm in one condition. The roulette wheel appears to be divided into either even or uneven pieces; however this uneven distribution is an inaccurate representation of probability of landing on a colour in all conditions. Selecting the bigger pieces are optimal choices, where the probability of winning is higher. This figure is adapted from Green et al., (2010).

To provide an analogue of these types of decisions with those faced in real life, consider the process of commuting to work. If you decide to drive, you control the speed of the vehicle, the route you take and how frequently you would like to stop in the middle of the journey. However, if you take the bus, you accept there are elements of this travel that you will have no choice over- from the speed, to the route to the number of stops being made. Of course, you still determine whether you would like to get on the bus, and at which stop you would like to step off, but there is clearly less perceived control over the outcome (arriving to work on time) in this scenario than driving. In reality, there may be factors beyond one's control (consider an earlier accident pile-up closing off a road) that impact on the outcomes which outweigh the impact of one's choices and control. Decisions that rely heavily on sensorimotor demands to execute these choices, may inadvertently increase one's perception of agency, above and beyond the task characteristics- feeling like one is in the driving seat rather than at the mercy of the bus driver.

1.2.3.2 Feedback for Decision-making

The previous work has shown the importance of task-relevant information in modulating choice selection. A critical source in learning about the task and how to optimise behaviour for it comes from the feedback we receive following an action. There is a critical distinction in the literature on motor control which distinguishes between two types of feedback- one indicated “knowledge of results” (a binary form of information i.e. was my action successful or not relative to the goal) and a second which provides information about the quality of the action – often referred to as “knowledge of performance” (Gentile, 1972; Kernodle & Carlton, 1992).

Whilst the former is often more readily implemented in the real world (think of a sports setting- it is much easier for a coach to indicate that an action was incorrect than state how it was incorrect) and is better than no feedback at all for learning (Travlos & Pratt, 2011), it is knowledge of performance that is the most optimal form of feedback.

Recent work manipulating these forms of feedback in decision-making has shown how this information can impact on reinforcement learning processes (i.e. in value update rate) and consequently bias decision-making. McDougle et al (2010) asked participants to complete a two alternate forced choice decision-making task under a variety of conditions. The probability of reward for each target and magnitude varied across trials but the expected value remained equivalent. In Experiment 1, they asked participants to make choice selections using a keyboard (pressing a left or right key to indicate a target). Here, they observed risk aversion – which, as highlighted in earlier sections, is typical in situations of uncertainty. In Experiment 2, participants had to make reaching movements towards the targets under two different feedback conditions- one in which knowledge of performance (or spatial feedback) was provided and a second in which only knowledge of results (binary feedback) was provided (Figure 1.6). The results show that participants adopted more risk-seeking strategies (choosing targets with lower probabilities of success and higher reward) when exposed to spatial feedback relative to the binary feedback conditions. Both conditions showed higher rates or risk propensity relative to the keyboard selection.

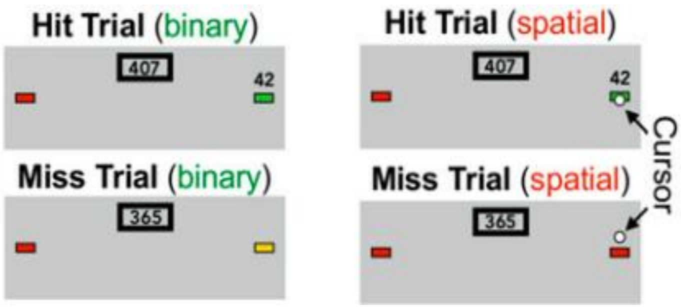

Figure 1.6 A sensorimotor decision task from McDougle et al. (2016). Participants are required to make a decision between two targets by reaching the target. There are two possible outcomes: hit and miss. In the Binary condition, participants are not shown the endpoint of a cursor. Instead they only see the points awarded. If it is a miss trial, participants do not receive any points. In the Spatial condition, participants are shown the endpoint of the cursor they control for both miss and hit trials. Image appears courtesy of McDougle et al. (2010).

The importance of feedback is of course well-established for sensorimotor learning (Keogh & Hume, 2012) and the ability to be able to interact in a precise and coordinated manner with the world around us is dependent on the richness of the available feedback (Burton & Rodgerson, 2001; Henderson, Sugden, & Barnett, 1992) but what the experiments by McDougle et al (2016) have shown is that the attenuation and amplification of information relevant to the sensorimotor domain can bias higher order choice selection.

1.2.3.3 Motor Competence

Another experiment reported by McDougle et al (2016) asked participants with cerebellar ataxia to complete the task. The authors reasoned that participants with limited ability to be able to correct the errors of their actions would mean that the manipulation of endpoint feedback would have no impact on their choice selection, given that it would provide information that the participants would not be able to take advantage of. Consistent with this prediction, they found cerebellar ataxia patients showed risk averse behaviour on the task relative to health controls. Given these findings, it seems that one's *ability* to be able to act on the information in the environment (which brings us back around to the importance of agency) is a critical part of the decision-making process and may thus co-vary as a function of one's motor competence.

Motor competence is often characterised through standardised batteries (Fransen et al., 2014; Rudisill, Mahar, & Meaney, 1993; Vedul-Kjelsås, Sigmundsson, Stensdotter, & Haga, 2012) that capture how quickly, accurately and smoothly one is able to interact with the external world. As predicted, in contrast to agency, research has shown that subjective perceptions of motor competence correlate well with actual motor ability (Robinson et al., 2015).

Whilst an examination of clinical patients with specific cerebellar impairments allows one to isolate sensorimotor competence, there are noteworthy difficulties with this type of approach. For example, patients with cerebellar impairments are a largely heterogeneous sample (Trouillas et al., 1997) and impairments in some cases can have an impact on related areas (see for instance, the earlier highlighted work showing the relationships between the cerebellum, basal ganglia and prefrontal cortex (Ghez, 1991; Riemann & Lephart, 2002); also see other studies showing the effect of cerebellum on cognitive functioning (Botez, Botez, Elie, & Attig, 1989; Ivry & Baldo, 1992; Leiner, Leiner, & Dow, 1991; Wallesch & Horn, 1990; Watson, 1978)); and recent demonstrations of how the cerebellum is central to the processing of a large variety of cognitive tasks; (King, Hernandez-Castillo, Poldrack, Ivry, & Diedrichsen, 2019).

An alternative approach using healthy participants may allow us to probe the impact of competency on choice selection without the problems inherent in the use of clinical samples. For instance, there is a plethora of evidence showing that when people use their non-preferred hand to perform a motor task, they are slower and less accurate at a variety of tasks such as writing, throwing and reaching compared to their preferred hand (J. Annett, Annett, Hudson, & Turner, 1979; Borod, Koff, & Caron, 2011; Duff & Sainburg, 2007; Fitts, 1966; Hammond, 2002).

Handedness is considered to develop pre-birth, becoming consistent during childhood (Fagard, 2013; Hammond, 2002; Serrien, Ivry, & Swinnen, 2006). The definition of handedness in the literature is consistently preferring to use one hand to perform a particular task where it is more skilled than the other hand (Hammond, 2002; Serrien et al., 2006). Even though individuals can train and use the non-preferred hand for certain tasks (Ackland & Hendrie, 2005), the non-preferred hand seems to generate slower reactions and greater inaccuracy compared to the preferred hand (Borod et al., 2011). Evidence suggests that non-preferred hand seems to generate more error while executing a motor task (J. Annett et al., 1979) which might lead to inaccuracy in execution. Thus, a simple manipulation of motor competence might be achieved by changing the hand they used to perform a motor task.

1.3 Thesis Structure

The previous sections have provided some brief introductions to core concepts related to action selection execution and we will lean on the ideas from these approaches in the following chapters of this thesis. These chapters are structured in the form of manuscripts, with each chapter linked by a core task methodology; will be given in details in Chapter 2 and Chapter 3, any important points will be addressed in the subsequent chapter.

The first experiment introduces a novel two alternative forced choice task that first isolates and then integrates action selection and execution into one decision making task. The task is inspired by the body of research on economic choice selection and the processes underlying sensorimotor execution presented above. This paradigm will allow us to examine the influence of feedback, motor competence and agency on decision-making in the subsequent chapters.

Together, the overarching collective goal of these studies is to better understand the bilateral relationship between parameters driving action selection and execution interact to produce decision-making. In this way, it is hoped that this thesis will provide a valuable contribution towards a growing body of research on decision-making demonstrating the importance of examining the intersection between action selection and execution.

Chapter 2 Manipulating Sense of Agency in a Motor Task

2.1 Abstract

A common observation is that participants seem to exhibit more risk-taking under conditions of uncertainty during sensorimotor decision-making experiments compared to cognitive tasks that have equivalent uncertainty. One possible explanation for this effect is that actions resulting in non-rewards in the sensorimotor domain infer an increased sense of agency - with execution feedback allowing participants to believe they can correct actions for future reward. To test this hypothesis, we designed a novel experiment which required participants to choose one of two moving targets (wide or narrow; the selection phase) which they subsequently intercepted (execution phase) for points. The wide target yielded fewer points but was easier to hit than the narrow one, with equivalent expected value. We manipulated agency over the execution phase using a within-subjects design with conditions presented in a random order. In the first condition, participants had no control over movement execution and watched the computer randomly trigger cursor movement to intercept the target. In the second, participants triggered the onset of the movement, but watched the target move at a constant speed. In the third condition, participants had full control over the movement onset and cursor speed. When participants had no control, or partial control there was no change in risk appetite; however, when provided with full control over execution, they showed heightened risk-taking. These data indicate that the high-risk propensity observed in sensorimotor decision tasks may be an inherent property of the agency afforded by action execution.

2.2 Introduction

Action selection has been widely investigated in experimental psychology (Newell et al., 2015), but the majority of work has focussed on economic choices (e.g. selecting one slot machine over another or, deciding between two mortgage options). As such, this phenomenon has largely been studied independent of action execution. There is now a growing body of literature recognising that motor control, that is, the systems involved in action execution, play a fundamental role in goal-directed decision-making and thus, modulate action selection (Wolpert & Landy, 2012).

The need to consider action selection and execution interactions can be illustrated through the following example. Consider a golf player working her way around a course. Her performance is not only the product of sensorimotor skill (action execution e.g. smooth execution of internal motor commands) but is also bound by decision-making. To select from a repertoire of possible actions, that is, decide what type of shot to execute and club to use, our golfer needs to consider whether the shot is to be played on the fairway or the rough, the target distance, wind direction and so on. Crucial to how these options are weighed up for action selection is the ability of the golfer to be able to *execute* the selected option effectively. A highly skilled player, believing in her own ability to determine a successful outcome is likely to prefer the potential gain of taking fewer shots to reach the hole, but a less skilled performer (and one who has less confidence in her own capabilities to control the outcome), may choose to avoid any hazards and favour the option of having more (relatively easier) shots. This example illustrates how the degree to which one is able to control the execution phase of the decision process could influence the selection phase. This chapter explores this concept through empirical examination of decision-making by manipulating the degree to which agents have control (or a “sense of agency”) of the execution phase and examines how this impacts the choices they make.

Definitions of sense of agency vary across psychology (and often delve into the realms of philosophy). Most commonly, agency may be defined as the belief in one's own capacity to act (Bandura, 1982; Friston et al., 2013), or the experience of a specific movement (Haggard, 2017), but most common, and the definition being operationalised here, is where sense of agency refers to being in control of one's own action (Haggard & Chambon, 2012b).

Building up an accurate internal representation (internal model) of the external environment is important for one to be able to determine the degree to which one has agency over the environment and is challenged by the impoverished and incomplete information that arrives through sensory input (Faisal, Selen, & Wolpert, 2008). To resolve this information uncertainty, one has to interact with the environment and understand the consequences of these interactions to develop more accurate internal models of the external world (Faisal et al., 2008; Green et al., 2010).

An empirical examination of this phenomenon comes from a study by Green et al. (2010) who asked participants to play a roulette game under two possible conditions. In one condition, the roulette wheel would stop automatically as determined by a computer and in the second condition, the stopping of the roulette wheel was determined by the participants through physical interaction. The authors observed that the participants in the latter condition were able to select more optimal decisions relative to the former (where higher probability of success was classified as optimal).

This sense of control over outcomes also determines our evaluations of another key driver influencing decision-making i.e. the evaluation of rewards and punishments. A basic tenet of reinforcement learning holds that action selections that elicit reward, increase in their value and increase the likelihood of repeating the action (selection and execution) and those that are punished are less likely to be replayed due to a reduction in stored value. Recent work has examined how this credit assignment process and thus subsequent actions are modulated by an evaluation of the degree of agency in action selection.

In a series of experiments by Parvin et al. (2018), the authors examined whether sense of agency could modulate the evaluation of reinforcements and punishments in a sensorimotor decision-making task that required participants to make shooting movements towards one of two targets with different payoffs, but equivalent expected value. One group of participants was told that the feedback following target selection was determined by the accuracy of one's motor execution, whilst a second group were informed that the outcomes were the product of the probability of payoff of the target (no sense of agency). In reality, outcomes across both experiments were predetermined.

Overall, the results indicated that participants were risk-seekers in the task where the accuracy of their motor execution seemed to be important. Additionally, instruction manipulation for the second condition (with no sense of agency) resulted in risk averse decisions. In these experiments, the authors suggest that a sense of agency meant that error was attributed to random variations in execution (motor noise) and thus, outcomes on individual trials were uninformative about the external environment and required only fine-tuning of one's internal model for motor execution. In contrast, for the condition where there was no sense of agency, the outcome on any given trial could be used to update the valuations of the targets. Parvin et al. (2018) has provided evidence that temporal dependence (the belief that a reward derived from a target would be similar to previous rewards from the same target) is low when there is sense of agency. Top down models of sense of agency suggest that motor errors are perceived as random noises because the environment is better understood and thus errors are less likely to occur and when they do, are more likely to be ignored.

Another study showed that the information presented at decision outcome could bias this value updating process (McDougle et al., 2016). In a conceptually similar two-alternate forced choice task, the authors presented results with either spatial information (indicating the degree and direction of the motor reach relative to the target region) or binary information (indicating that the reach to the target was successful or unsuccessful). When outcomes were presented including spatial information, participants had a prediction error signal they could use to correct subsequent choices. This resulted in a marked increase in participants' risk appetite relative to the binary feedback condition, which limited participants' capabilities to refine their motor commands.

The performance of a system depends on various contributions of the system's components. Feedback can be one of them. Fundamentally, there are two main forms of feedback: extrinsic and intrinsic. Extrinsic feedback has external information on agent's performance (Schmidt & Lee, 2005) whereas intrinsic feedback is considered proprioceptive (Annett, 1961). If the result of knowledge has no external information on performance, it can be classified as intrinsic feedback. After a failure, the movement adjustment would rely on intrinsic feedback if people do not see their own performance externally, which is an example of knowledge of results. People do not see their own performance but they see if the trials were a success or a fail. Thus, they need to rely on their instinct to make a better movement. In the current study, participants have to rely on the intrinsic feedback in the binary feedback condition, however, the performance has been represented externally in the spatial feedback condition.

The present study investigates whether manipulating the degree of control over the execution phase of a decision-making experiment could influence choice selection. A novel variant of an interceptive timing task (Giles et al., 2018) was designed to separate action selection, execution and outcomes. Specifically, on every trial (with a total of 300) participants were presented with two targets that varied in length and asked to make a selection for the target they would like to intercept in the next phase of the trial: a 1 degree of freedom movement task. The length of each target determined its “riskiness” based on the self-evident information that a smaller target would be harder to hit than a larger target. Participants were also explicitly informed of this relationship and further told that smaller targets would lead to greater rewards relative to larger targets. The task simulated the characteristics of a canonical decision-making task in which reward probability and magnitude are manipulated to pit riskier and safe options on a trial-by-trial basis.

Control in the interception phase was manipulated, such that participants could have complete agency over movement onset and execution (referred to as “Complete” agency), control only over movement onset (“Partial” agency) or simply watch the computer attempt to hit the target at a constant velocity and random movement onset (a condition with “None” agency).

Based on the findings of McDougle et al (2016), it was predicted that agency effects would interact, and be compounded by, outcome presentation. Specifically, it was expected that participants would exhibit a risk-seeking decision profile if presented with an environment with a high degree of control and presented with spatial feedback on their outcomes. The feedback could be used to allow participants to reduce their uncertainty about how to interact effectively with the environment and the complete agency condition would allow them to exploit this information to maximise reward. In contrast, the presentation of binary feedback (success/failure) in a low-control environment would increase uncertainty about the environment and removing the ability to correct action selection would result in risk-averse decisions.

2.3 Experiment 1

2.3.1 Sample

Thirty-three people (aged 20-47 years; M: 28.27, SD: 7.40; 23 Female) from the University of Leeds School of Psychology Participant Pool were recruited to the study. The Edinburgh Handedness Inventory (EHI) was used to assess participants handedness (Oldfield, 1971). Three people were classified as left-handed (EHI < -40), 1 person ambidextrous (-40< EHI<40) and 29 people were right-handed (EHI > 40). All participants reported normal or corrected-to-normal vision and, no neurological or psychiatric history. Participants attended the laboratory once and gave consent to take part in the study. All participants provided informed consent to the experimental procedure in accordance with ethical guidelines set out by the British Psychological Society (BPS). The study was approved by the School of Psychology Research Ethics Committee (reference: 17-0228). Participants were told they would be remunerated between £7 and £10 based on their performance from 10 random trials and overall performance, but all received £10 after the study.

2.3.2 Experimental Task

This multi-trial, multi-stage task involved a classic interceptive timing task being combined with the characteristics of a classic two-alternate-forced-choice task. In the first stage of the trial, participants had to make a decision between which of two targets they preferred to select. The targets varied in width and this width related to the probability of hitting the target. In the next stage the selected target started moving horizontally along the screen (after 600 ms, the target disappeared as it moved along a fixed trajectory and a cursor would move (under one of three control conditions, described next) to intercept the target in a fixed region of the screen. The target would reappear following movement termination, with feedback (described below) indicating whether the cursor had successfully interacted the target or not (Figure 2.1). Movement termination is when the cursor reaches the blue line where target moves.

The control of the cursor was manipulated, and participants were exposed to three different conditions. In the “Complete” agency condition, participants had to intercept the moving target using a stylus by (a) accurately anticipating the timing of the target to the zone and (b) moving the cursor towards the target with appropriate velocity. In the ‘Partial’ agency condition, participants only require deciding when to launch the cursor by clicking the mouse button. Then the cursor moved towards to target automatically. In contrast, in the “None” agency condition, the experiment initiated movement onset and controlled the trajectory at a constant speed 1000 mm per second. The idea of timing task was derived from removing the movement part from the task and control the timing part of interceptive timing task. Every agency condition had 100 trials so, every participants had 300 trials overall.

To investigate whether outcome presentation interacted with agency, participants were exposed to either spatial or binary feedback. In one condition, participants were provided with “binary feedback” where participants were informed only whether the cursor hit or missed the target. A “spatial feedback” condition provided information on the endpoint of the cursor and target location, thus indicating the degree and direction of the motor error.

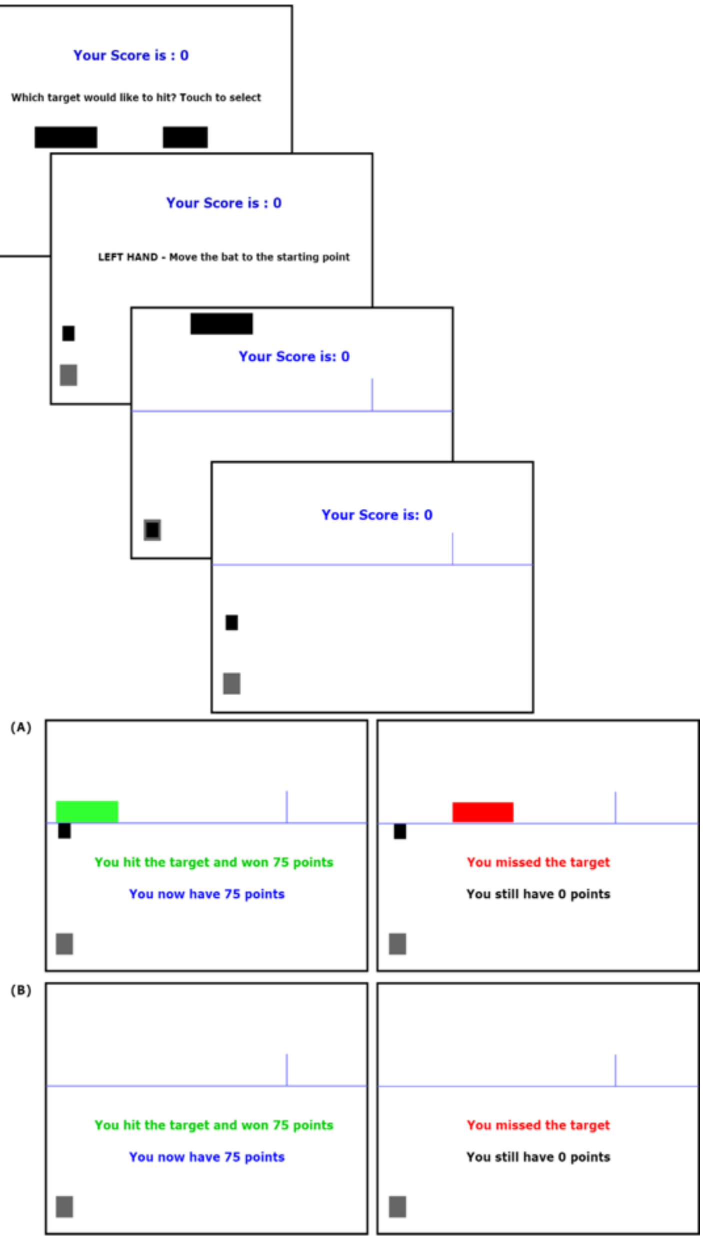

Figure 2.1 Interceptive decision-making task schematic. The schematic for left-handed participants is represented here (for right-handed participants, the screen was mirrored). The task started with participants making a decision between two targets by tapping on one to indicate selection. Participants susbequently moved a cursor to a starting position towards the bottom corner of the screen. After a random interval between 0-1-0.5 ms, the previously selected target appeared and moved across the screen at a constant speed towards a blue line (0.6 ms). Once the blue line was reached, the target became invisible (0.9 ms). The participant had to estimate the point at which the target could be intercepted by moving the cursor towards the future location of the target (the "interception point") by moving the cursor target in a straight vertical line (the cursor position was restricted to one degree of freedom). After the cursor passed through the interception point, participants were provided with feedback about the outcome of the trial (hit/miss and points). The feedback screens for the spatial and Binary conditions are represented in Panels A and B respectively.

2.3.2.1 Reward Schedule

As the focus of this experiment was on whether action selection for reward could be manipulated by agency, we needed to control for individual differences in interceptive timing ability. To this end, reward schedules were surreptitiously manipulated and predetermined. Both outcome (i.e. the hit probability associated with each target) and reward were based on target size (Figure 2.2) such that the expected value was matched in every trial and kept constant throughout the experiment. For example, in one trial, a “safe” target with 91% hit probability and reward value of 40 points would be paired with a risky target that had 15% hit probability and rewarded 242 points. In both cases, the expected value was approximately 37. Risk was operationally defined based on the probability of hitting the target. Participants received the associated reward value on hit trials whereas no points were rewarded on the miss trials. The targets’ location was counterbalanced. Target pairs were randomly displayed for each participant, so every participant saw the target pair in a random order.

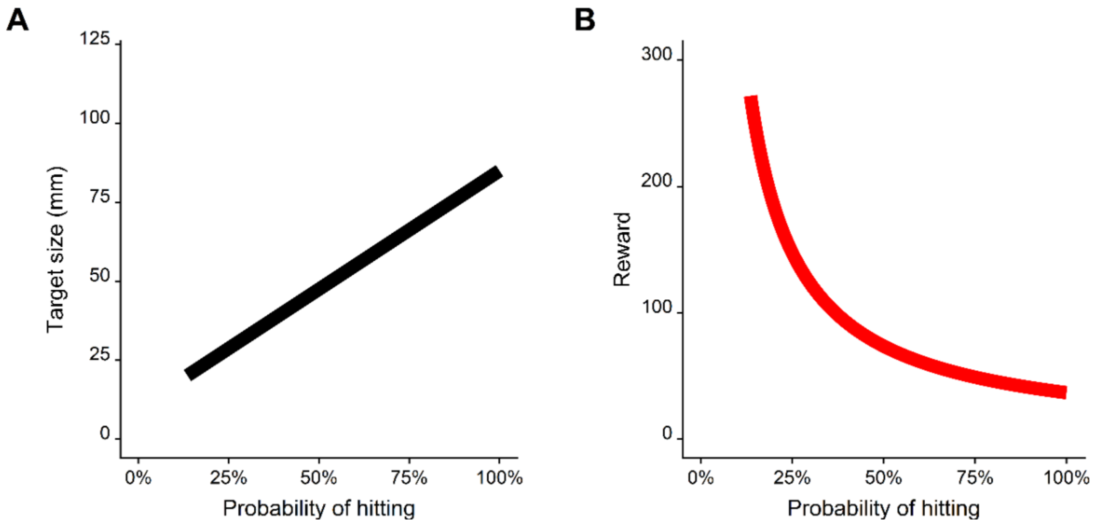

Figure 2.2 Target size, probability and reward magnitude. (A): The relationship between probability and target size. It is a linear relationship. When the target size increases, the probability of hitting the target increases. (B) The relationship between reward and probability of hitting. When hitting probability increased, the magnitude of reward decreased.

To fix the hit rate between participants, outcomes were predetermined. As such, it was important to control feedback presentation. On some trials, where the predetermined outcome matched the actual outcome, the feedback was ‘veridical’. On other trials, where the predetermined outcome did not match the actual outcome, feedback was manipulated unbeknownst to the participant and participants were provided with false hit or false miss feedback. In the spatial feedback condition, in the false hit feedback, the location of the target was positioned based on a uniform distribution from the width of the target. In the false miss case, the direction of left or right was randomly selected. The error size is uniform distribution (0,50) where all possible errors of a random location between 0 to 50 was equally likely to occur. This principle was applied even in the ‘None’ agency condition where the cursor was automatically played by the computer.

2.3.2.2 Subjective Measures

Participants were asked to complete a post-experiment survey at the end of each condition (Complete, Partial, None). The survey (using a 7-point Likert scale) required participants to state the extent to which they agreed with the following three statements: “I felt in control of the outcome of the task”; “I was risk-seeking during the task”; and “The game tracked my movements accurately”. The first question was to assess the subjective control and the second was to assess subjective riskiness. The last question is to make sure if there was a technical problem on connectivity of the tablet with the stylus.

2.3.3 Apparatus

The task was shown on a 15.6 inch laptop with a screen resolution of 1920x1080, were 1 cm on the screen corresponded to 56.4 pixels. Participants used a stylus to move the cursor on a Wacom Intuos 4 large tablet with 12 in x 18.2 in active area. The stylus was used on the screen directly. The task was programmed using Python 3.7.2.

2.3.4 Study Design

A two (feedback type; Binary and Spatial) by three (Sense of Agency; Complete, Partial, None) mixed subject study design was employed. Participants were randomly assigned to two different groups: either, binary feedback condition or spatial feedback condition. The participants in each group performed the tasks in three different conditions: Complete, Partial, and None.

2.3.5 Procedure

The experiment took place in a laboratory in the psychology department of the University of Leeds. Participants attended one experiment session including 3 blocks of 100 trials. The sense of agency manipulation (Complete, Partial and None) varied across blocks and the order was counterbalanced across participants. After each block, participants answered the post-experiment survey detailed above.

2.3.6 Statistical Analysis

2.3.6.1 Preliminary Analyses

A series of preliminary analyses were performed to explore whether there were any differences in age (given that this can be an important factor in risk taking, with risk propensity declining with age) (Deakin, Aitken, Robbins, & Sahakian, 2004; Dohmen et al., 2011; Mandal & Roe, 2014; Mata, Josef, & Hertwig, 2016; Quetelet, Knox, & Smibert, 2013; X. T. Wang, Kruger, & Wilke, 2009) and participants subjective experiences of the experimental manipulations. Age difference across groups (spatial and binary) was tested using a student’s t-test to make sure that group samples were of comparable age. Participant responses from the survey were compared between conditions through a repeated measure ANOVA (Sense of Agency; Complete, Partial, None) (see an example of this in Berberian et al., 2012; Wen et al., 2015) regarding subjective riskiness and subjective control to investigate subject perception of their own riskiness and to explore how the agency manipulation was perceived by participants. Lastly, to investigate if participants differentiated the subjective control question from the technical connectivity (if the game captured the stylus movement), pearson's product moment correlation was conducted.

2.3.6.2 Primary Analyses

The dependent variable was the amount of risk propensity participants displayed in the task. On any given trial, participants' selections could be either risky or safe. If participants selected the target with smaller width on a trial, their response was considered as risky, otherwise the responses on the given trials were considered as safe. The mean of the participant riskiness was calculated as the sum of risky choices divided by the trial number –after removing failed trials- which was used for analyses. Based on Z scores of mean of riskiness with -1.96 to 1.96 cut off, 3 participants were removed.

In addition to the experimental manipulation, the order of conditions was added to the analyses to investigate if there was an effect of an order on decision making. Since there were three conditions (Complete, Partial and None), there were six possible orders. In order to statistically investigate the effect of these factors on participants' selection a 2 (Feedback type; Spatial feedback, Binary feedback) x 3(Sense of agency; Complete, Partial and None) x 6(order; Complete-Partial-None, Complete--None-Partial, None-Partial-Complete, None-Complete-Partial, Partial-Complete-None, Partial-None-Complete) ANOVA was performed.

The ezANOVA package in R was used to run analysis of variance. Bonferroni correction was used for pairwise t test for post-hoc test. An alpha threshold of <.05 was accepted for significant results in the current study and the rest of the studies presented in this thesis.

To provide a measure of effect size, generalized Eta- Squared (η_G^2) is reported. Generalised eta squared consistently shows smaller value compared to the more often reported partial Eta-squared measure but it is considered to be a more appropriate index for repeated measures designs (Bakeman, 2005). Guidelines suggest that scores of 0.02 indicate a small effect size, scores of 0.13 as medium and, scores of 0.26 and greater as large effects (Bakeman, 2005). We use this measure and these effect size guidelines for each study reported in this thesis.

Mauchly's Test of Sphericity was used to indicate if the assumption of sphericity had been violated for repeated factors in the ANOVAs. Levene's test was used to assess for homogeneity of variance.

Based on the results observed in previous experiments in this area, we expected to find a medium effect size ($\eta_G^2 = 0.13$; Cohen's d = 0.5 (Cohen, 1988)) for the primary outcome of sense of agency and feedback. To obtain statistical power of 80%, with a medium effect size in this experiment design, G*Power (Erdfelder, Faul, Buchner, & Lang, 2009) indicated a minimum of 24 participants was required. It is worth noting that this sample size also aligned with a similar study (McDougle et al., 2016) , which recruited 20 participants for each group.

Lastly, it is possible that participants might have been sensitive to target size differences because of the reward gap between targets. For example, when the difference between two target sizes was extremely high, participants might approach a different strategy for target selection than when the target size difference was extremely small. To investigate, a correlation for riskiness and differences in target sizes was conducted.

2.4 Experiment 1 Results

2.4.1 Preliminary Analysis

There was no difference ($t(26.4) = -1.06$, $p = 0.299$) in age in the binary feedback condition (M=26.88, SD=5.26) and Spatial condition (M=29.59, SD=8.81).

In order to ensure whether agency manipulation was successfully delivered, the subjective control scores were compared between each agency condition. A repeated measure one-way ANOVA was conducted on subjective control responses (where participants feel in control of the task) (Carifio & Perla, 2007). The result showed a difference between conditions [$t(26) = 18.28$, $p< 0.01$, $\eta^2_G = 0.22$]. A pairwise t test showed that participants reported that they felt more in control of the task in the Partial (M = 4.42, SD= 1.58, SE= 0.28) and Complete (M = 4.36, SD= 1.67, SE= 0.29) conditions compared to None (M = 2.67, SD= 1.57, SE= 0.27) respectively $p<.001$, $p<.001$. There were no differences in degree of control between partial and complete conditions.

In order to investigate participants' subjective riskiness scores between each agency condition, a repeated measure one-way ANOVA was conducted on this survey measure. The subjective riskiness scores indicated a similar trend. Mauchly's test indicated that the assumption of sphericity was not violated (W= 0.92, p= 0.33). The result showed that there was a difference between conditions [$F(2,62) = 3.96$, $p = 0.02$, $\eta^2_G = 0.04$] (Figure 2.3). Participants felt more risky in the partial (M = 5.03, SD= 1.47, SE= 0.26) condition compared to execution (M = 4.61, SD= 1.89, SE= 0.33), none (M = 4.15, SD= 1.80, SE= 0.31) condition but these differences were not statistically significant (p's > .13).

Lastly, there was no correlation between subjective control and game capturing stylus movement ($r = 0.074$, $p = 0.463$), which might mean that the participants have perceived subjective control questions differently than game capturing stylus movement as expected.

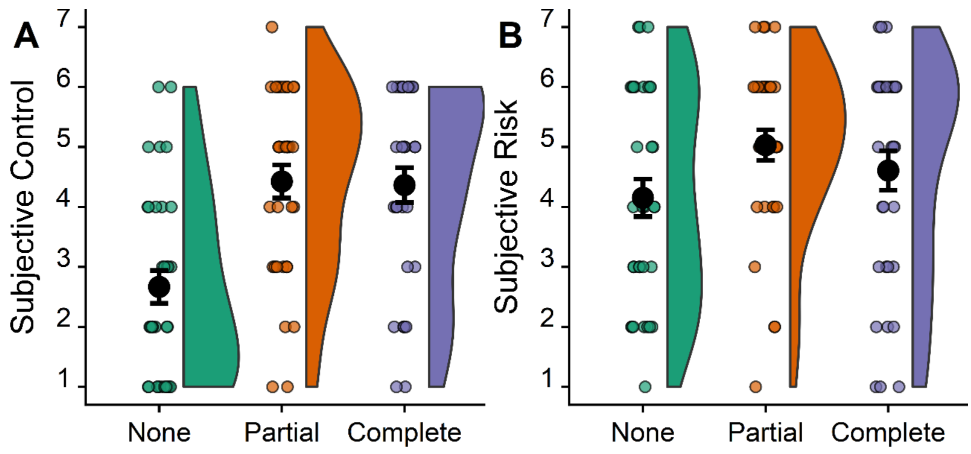

Figure 2.3 Agency and Subjective Measures of Control and Risk. (A) Participants rated if they felt in control of the outcome of the task. The graph shows that more people rated they totally agree that they are in control of the outcome of the task in complete and partial condition, whereas, in their rate decrease when they performed none condition. B) Participant rated how risky they think they are in each session. The subjective perception of their own selection is also aligned with the subjective control ratings. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean. The colour represents the different agency conditions.

2.4.2 Primary Analyses

A 2 (Feedback type; Spatial, Binary) by 3 (Sense of agency, Complete, Partial, None) by 6 (Order, counterbalanced session orders) ANOVA was conducted. Mauchly's test indicated that the assumption of sphericity was not violated (W= 0.99, p= 0.91). There was no main effect of agency [$F(2,36)= 1.88$, $p = 0.17$, $\eta^2_G = 0.03$], feedback [$F(1,18)= 0.30$, $p = 0.59$, $\eta^2_G = 0.01$], or order [$F(5,18)= 0.65$, $p = 0.66$, $\eta^2_G = 0.10$] (Figure 2.4). However, there was an interaction between order and agency [$F(10, 36)= 2.75$, $p=0.013$, $\eta^2_G = 0.22$)]. To investigate this interaction, the data were divided by the combination of order and condition. Each group was classified by which sense of agency condition they underwent in which block. For example, people in the complete condition were compared with participants who had the complete condition at the first block, participants who had the complete condition at the second block and people who had the complete condition at the third block. For each agency condition the first, the second and the third group was compared via a one-way ANOVA.

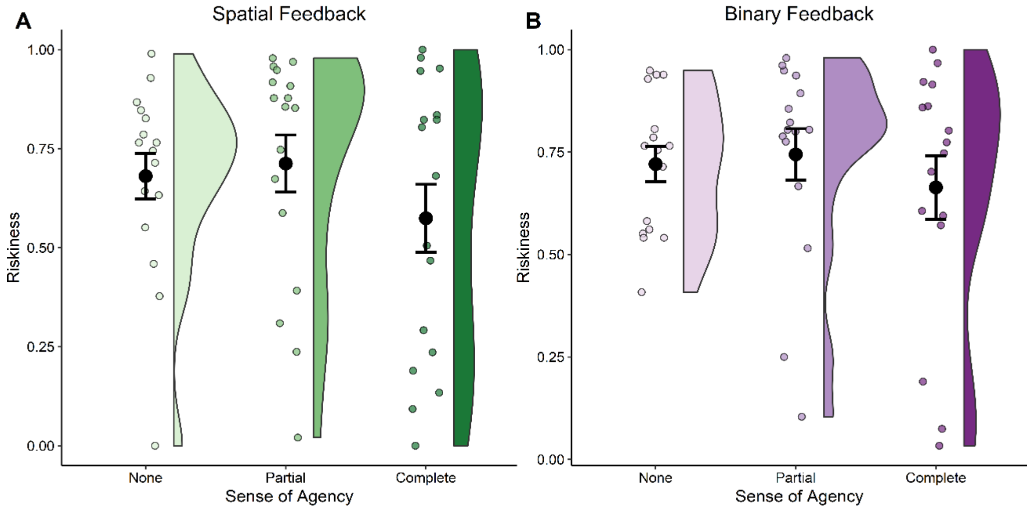

Figure 2.4 Risk propensity for each condition. The graph shows the mean of participant risky selections in different conditions. Participants mainly selected the risky target over safety, target in all conditions. There is a bigger variation in selection of risky target in complete condition where people also can see the knowledge of performance, spatial feedback. The results show no significant differences between these conditions. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean. The colour shades represent the different agency conditions.

In the complete condition, the Levene test result showed that the homogeneity of variance was not violated [F(2,27)= 2,64, p= 0.089]. The main effect of the order was significantly different [F((2,2))= 4.70, p= 0.018, η_G^2 = 0.25] (Figure 2.5). To investigate which groups were different, we conducted a post-hoc test. Participants who were exposed to the complete condition first showed different behaviour (more risk averse) than participants who were exposed to the complete condition last (p=0.015). Participants were exposed to the complete condition in the middle of the experiment did not differ from participants who were exposed to the complete condition either first or at last. In the partial and none condition, there was no significant different between orders (Partial [F(2,27)=2.14, p= 0.14, η_G^2 = 0.14)] and None [F(2,27)= 0.22 p=0.81, η_G^2 = 0.02]).

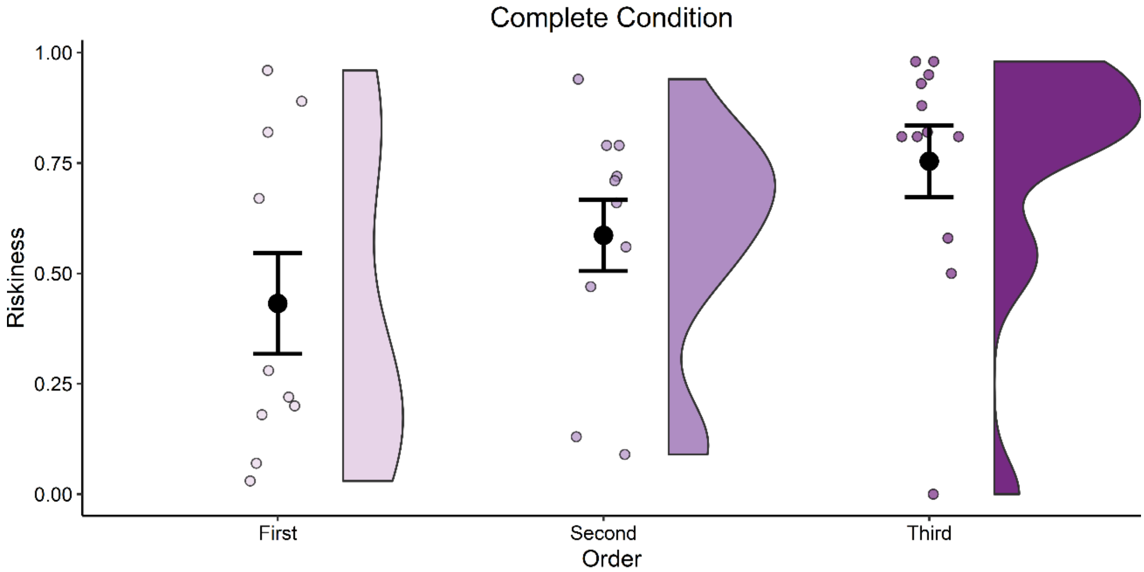

Figure 2.5 Differences in risk propensity as a function of task order. Participants' riskiness level in complete condition. Participants who exposed to the complete sense of agency at first were risk averse compared to participants who received complete sense of agency second or last. It looks that participants became riskier over time. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean. The colour represents the different groups.

The target size differences per target pair differed throughout the experiment. For example, in some trials participants had to select between two targets whose hit probability was figuratively 56 versus 48 while in others, it was 35 versus 78. In the former, the difference between risky and safe target selection was small and in the latter it was large and this difference might have impacted on risk propensity. To explore this relationship between risk magnitudes (operationalised as difference in size between the target pairs) a Pearson's product moment correlation was conducted. We found no relationship between difference in target size and riskiness (r (23) = -0.20, p =. 34; see Figure 2.6).

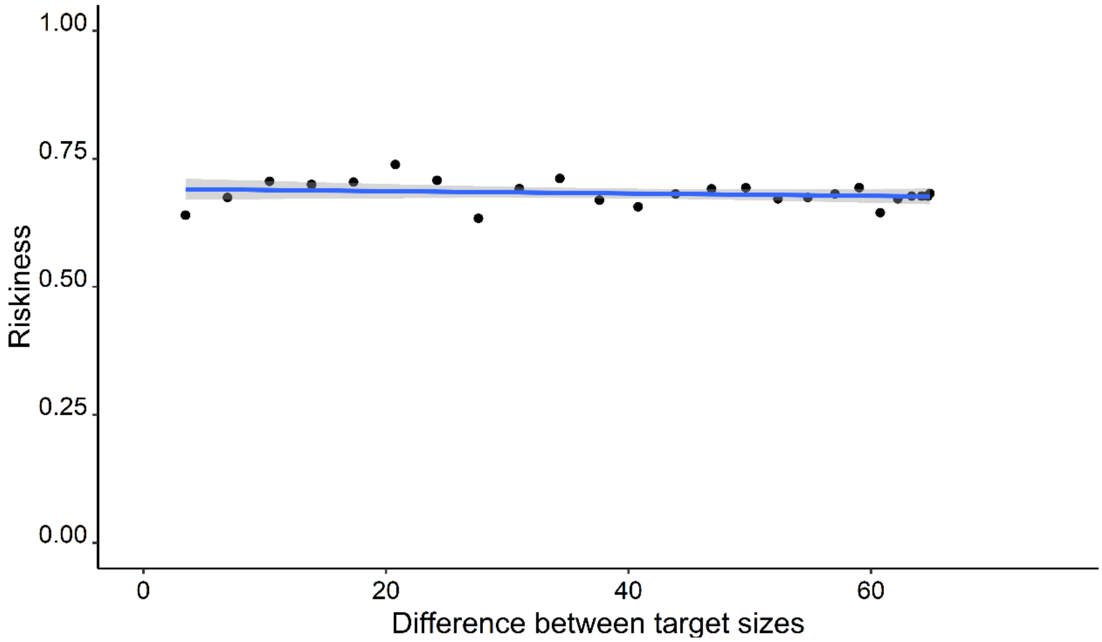

Figure 2.6 Correlating target Size and Riskiness. Target size per target pair varies 25 times. The correlation between these two is very small. Every dot represents the risky target selection on average of the difference between target pair. The difference between target pair is not related to how risky participants are. Participants are mainly risky regardless of how big the difference is between the target sizes.

In summary, there was no main effect of feedback and sense of agency; however, there was an interaction between sense of agency and order. The interaction was driven by behaviour in the complete condition. Participants who performed in the complete condition first exhibited a more risk-averse behaviour than participants who exposed the complete condition last.

Table 1 Values for means, standard deviations and standard errors in all three conditions.

Condition	Condition	Mean	sd	se
	First Block	0.63	0.26	0.07
None	Second Block	0.72	0.18	0.05
	Third Block	0.72	0.14	0.04
	First Block	0.66	0.24	0.07
Partial	Second Block	0.62	0.34	0.10
	Third Block	0.85	0.14	0.04
	First Block	0.43	0.36	0.11
Complete	Second Block	0.59	0.27	0.08
	Third Block	0.75	0.28	0.08

2.5 Discussion

The present study sought to investigate whether choice selection (and specifically risk propensity) could be influenced by agency and feedback presentation in a sensorimotor decision task. Consistent with the hypotheses, sense of agency seemed to influence riskiness of decisions. However, specifically, only the complete agency condition led to participants exhibiting different risk propensity profiles. Participants who had complete agency in the last block were much more risk seeking than participants who had complete agency in the first block. Contrary to previous work, this study did not observe differences between feedback types in terms of altering propensity to make risky decisions.

The most obvious finding to emerge from the analysis was the interaction effect of agency and the block order. Participants that received the complete condition first behaved in a rather safe manner compared to participants that received complete condition last. The given order of complete condition had an effect on their risky choices. A possible explanation for this might be that participants were naïve when they started the experiment. Hence, they did not have an accurate internal model about the task environment such as target properties. The task was new for them. They might have needed to explore the task properties and their own motor performance; hence choosing safer options at first. Trial by trial, the internal model about the task environment would have been improved. Participants who were exposed to the complete sense of agency during the last block had an opportunity to act based on the internal model rather than every specific outcome. Hence, failure in the task might be ignored (Green et al., 2010; Parvin et al., 2018). When the internal model is generated, the agent's behaviour would be based on the internal model instead of every single outcome derived from each single trial. Therefore, when they have one failure from one single trial, they might actually ignore the failure and still go for a risky option. It is possible, therefore, that the participants in only the complete sense of agency condition became more risk seeking. Analysing participants' sensitivity to previous outcome can be achieved by calculating how often participants switch from previous trials based on an outcome. In the current study, the study design fails to investigate how participants switch their behaviour after every trial feedback because there was not enough trials to investigate this interaction.

What is surprising is that participants were more risk seeking than expected in the condition where there was no sense of agency. This result is contrary to previous studies which suggested that people are more risk averse when people perform classical decision making tasks (McDougle et al., 2016). There are a number of notable differences between the McDougle et al. (2016) task and the current task. Firstly, the target properties were visually clear in the current study, unlike McDougle et al. (2016).

In the current task, participants were informed that the larger target is related to the high probability of hitting the target and the small target is related to low probability of hitting the target. Additionally, in the current study each target pair had information about the probability of hitting the targets; however, targets in McDougle's task were visually the same and there was no clue about the probabilities of each target; the targets' properties remained uncertain. Thus, participants performed the task under risk rather than uncertainty. This may explain why people were risk seeking in the current study. It is clear that people generally try to avoid uncertainty (Pleskac & Hertwig, 2014), which results in not exploiting the target (Heath & Tversky, 1991); however, knowing the target probabilities, as in the current study, might result in more exploitative risk-seeking behaviour.

A key goal of the study was to compare riskiness across different levels of sense of agency. Thus, we needed to control other parameters such as expected value between alternates. To do that, we needed to fix the probability of hitting the targets. The reason we exposed participants to pseudo-veridical feedback is to control for different levels of motor variability. Some people might be naturally better at intercepting the target than others and so experience different rates of success. This sort of variability could influence the selections and contaminate the result; however, knowing that motor variability in action increases uncertainty, which affects decision making (Wolpert & Landy, 2012). A further study might be necessary to investigate the effect of motor variability on decision making (see Figure 3.3).

Contrary to prior studies that noted the importance of feedback type (McDougle et al., 2016), the results of this study did not show this effect. A possible explanation for this difference might be that when there was manipulation of agency, participants might not attribute the feedback outcome to their performance. The difference between expected outcome and actual outcome might be modulating the relationship more than the feedback (Wen et al., 2015). Moreover, it is also possible that people might have a sense of agency even though they do not actively perform in a motor task (Wegner, Sparrow, & Winerman, 2004) when there is a discrepancy between predicted feedback and actual feedback; people are prone to misattribute a sense of agency to an external source or vice versa (Sato & Yasuda, 2005), which might cause a failure in sense of agency manipulation. In this study, the subjective control scores, participants reported similar experiences of control between partial and complete condition. This might contaminate the results in that participants might feel more in control when they have positive feedback rather than negative feedback. This might require another study where there is no sense of agency manipulation.

In summary, a sense of agency impacts on decision making, independent of feedback type. A high level of sense of agency might modulate risk seeking. In an unknown environment where people do not have an internal model of the external world, people might be risk averse, whereas, a high level of sense of agency might result in risk seeking behaviour after some experience. Since, sense of agency can be affected by unexpected feedback, we need to investigate the effect of actual performance on the decision making.

Chapter 3 : Execution Error Feedback and Risk Propensity

3.1 Abstract

The study reported in Chapter 2 indicated that decision making may be impacted by intrinsic factors such as the ability to control the execution of a motor task (i.e. agency). The process of motor execution is a dynamic one that also requires extrinsic sensory information from the environment for successful execution. In this way, external information that can be used to guide sensorimotor actions may also influence the decision-making process. The experiments reported in this chapter aimed to investigate the effect of extrincsic sensory information on decision making (feedback). The previously presented two-alternate-forced-choice task was employed here while feedback was manipulated by varying the amount of information participants were provided with at decision outcome. When participants were provided with complete information about their performance, they were more likely to make a risky selection than participants who were only given binary information about their performance. This effect holds when the outcomes were with both veridical and predetermined feedback; expected value for each target kept constant.Receiving more information about ones execution error was also related to better error correction.. This work extends previous findings from Chapter 2; as well as intrinsic factors, extrinsic factors such as the amount of externally presented feedback can have on decision making. Receiving execution error signals as external feedback (spatial feedback) seems to result in an increase in risk-seeking behaviour as well as better error correction compared to binary feedback.

3.2 Introduction

A basketball player approaching the opposing team's basket has to decide where on the court to throw the ball from, since this will determine the number of points they will be awarded for a successful throw. If she makes a successful throw from outside of the three-point line, the team will receive 3 points. If the basketball player takes a successful shot from inside the three-point line, the team earns 2 points. Clearly, shooting from beyond the three-point line is riskier, as it is less likely to end with a positive outcome because of the distance between the net and the player. Now, imagine a basketball player being asked to shoot blindfolded and thus, being unable to see where the ball ends up. It would be expected that most people would shoot from inside the 3-point boundary line, and in fact from as close to the hoop as possible. However, perhaps if you are Kyle Korver or Stephen Curry and possess exceptional abilities, then it could be speculated that they may well venture to shoot from outside this boundary. This illustrates an obvious interplay between sensorimotor competence and task demands, when it comes to decision-making for a particular task. A blindfold reduces online information while throwing a ball so the player is reliant on their internal models/ or prior information, which may well be sufficiently good enough to use to carry out the action accurately for a professional basketball player and may push them to adopt a riskier approach.

In classical decision making studies discussed in the first chapter, people tended to be more risk-averse in order to avoid losses (Wisniewski, 2000). However, those studies largely involved little or no focus on action execution (i.e. the sensorimotor component of decision-making). There is a growing body of research focusing on the relationship between motor control and decision making. Motor control is computationally considered equivalent to decision making (Wolpert & Landy, 2012), and motor control studies provide some evidence that people might adopt an optimal behaviour while making a decision (Trommershäuser et al., 2005). There is still a big gap in the current literature on the effect of feedback on risk propensity.

Feedback clearly has a pivotal role in motor control (Keogh & Hume, 2012) with many studies showing that the *type* of feedback has an effect on motor performance (Wulf, Shea, & Lewthwaite, 2010). Extra information through feedback might increase the speed of learning (Wolfram Schultz, 2017), with faster learning equalling better motor execution. As we illustrated in the general introduction, McDougle et al. (2016) manipulated the type of decision-making feedback given to participants, who were making a decision that required the execution of an action (reaching a target). The participants were given one of two types of feedback: *Spatial* and *Binary*. Spatial feedback gives information on the motor execution error: how far an agent was to the success. Whereas, Binary feedback gives information only on whether they hit or miss. The results demonstrated that respondents in the Spatial condition, made significantly more risky choices compared with those in the Binary condition. It is important to note that motor control as well as the sensory information might affect decision making (McDougle et al., 2016).

Performance might be a factor manipulating risk propensity. Someone who performs well would have a higher hit rate. Consequently, the very same person would have different expected values (EV) compared with someone who performs poorly, which might result in adopting different strategies in terms of risk. Since a higher hit rate would result in higher expected value, the former person could optimize their selection and go for a risky target. Thus, motor control can be sensitive to optimizing decisions (Neyedli & Welsh, 2014). This might confound the researchers' ability to compare the effect of feedback type on risk propensity. In this chapter, the effect of feedback type on decision making will be explicated to enable better understanding of the decision making mechanisms. This requires having participants at the same level of motor performance; it is also important to investigate the relationship between feedback type and motor performance.

In this chapter, there will be two studies investigating the effect of the individual variability of performance and the effect of feedback. We hypothesise that (1) participants who are in the spatial feedback condition will have a better performance (hit rate), as they have more information about their performance, also (2) since these participants will have a better performance, they are more likely to be risk seekers. Being exposed to execution error, would lead to riskier future selections; therefore, those receiving spatial feedback would select riskier choices. Spatial feedback and binary feedback have different information levels; spatial feedback gives extra information on the execution error, whereas binary feedback has only the information of hitting or missing. Spatial feedback would give less uncertainty about motor execution than binary feedback. This might mean people attribute the error to their execution more in the spatial feedback condition. In Experiment 2 participants are given predetermined feedback (i.e. feedback independent of performance) to make sure they have a similar hit rate to fix the expected value. It is also hypothesised that the participants in this spatial feedback condition will be more likely to be risk seekers.

3.2.1 Experiment 2

3.2.1.1 Sample

Twenty-five adults (aged 18 to 33 years; M = 20.64, SD = 4.46; 23 Female) were recruited from the University of Leeds Dentistry Department. The Edinburgh Handedness Inventory (EHI) was used to assess participants handedness (Oldfield, 1971). Two people were classified as left-handed (EHI < -40), 8 ambidextrous (-40< EHI<40) and 15 people were right handed (EHI > 40). All participants reported normal or corrected-to-normal vision. All participants took part in the study as a part of dentistry application. The approval was obtained from the local research ethics committee (Reference 271016/MM/216).

3.2.1.2 Experimental Task

The same interceptive decision-making task employed in 2.3.2 was used for this study. This was a multi-stage task incorporating a classic interceptive timing task combined with the characteristics of a classic two-alternate-forced-choice task. The first stage of the trial started with participants selecting one of two targets (target pair) based on preference. The two targets varied in width, with greater width increasing the probability of hitting the target. Next, the selected target moves horizontally along the screen (after 600 ms, the target disappears as it moves along a fixed trajectory). The participants move a cursor to intercept the target in a fixed region of the screen. The target would reappear following movement termination, with feedback (described below) indicating whether the cursor had successfully interacted with the target or not on the blue line (Figure 2.1). In this study, target pairs were represented in the same order for every participant. Additionally, the hit rate was not fixed. Feedback on all trials was veridical.

Every participant had 100 trials. Target pairs represented in an order where the magnitude of reward and target size were equal for both targets. Then, one gradually increased while the other gradually decreased. The former one peaked in terms of reward at trial 25 (vice versa in terms of target size), then started gradually decreasing until the target size and reward magnitude were equal at trial 50. After 50 trials, the magnitude of target pairs and target size was equal again. This is called one cycle of trial representation and there were two cycles of trial representation.

Conditions were classified based on the type of the feedback presented to participants at action outcome (Spatial feedback and Binary feedback). In the binary feedback condition, participants were informed only about whether they hit or miss the target without any other visual cues about their performance. In the Spatial condition, participants were able to see spatial information regarding their error.

3.2.1.2.1 Subjective Measures

Participants were asked to complete a post-experiment survey at the end of each condition. The survey (using a 7-point Likert scale, where 7 was totally agreed and 1 is totally disagree) required participants to state the extent to which they agreed with the following three statements: “I felt in control of the outcome of the task”; “I was risk-seeking during the task”; and “The game tracked my movements accurately”.

3.2.1.3 Apparatus

The task was presented and completed on a 11.6″ tablet PC with a resolution of 1366x768 (1 cm on the screen corresponded to 54 pixels). Participants used a stylus to move the cursor on the screen directly. The task was programmed by using Python 3.7.2.

3.2.1.4 Study Design

A between subject study design was employed to avoid information transfer from spatial to Binary conditions. Participants were randomly assigned to two one of two different groups; binary feedback group and, spatial feedback group.

3.2.1.5 Statistical Analysis

3.2.1.5.1 Preliminary Analyses

The groups were tested in terms of normality by Shapiro-Wilk Normality test and the equality of variance. If these assumptions had not been violated, the age differences between groups (spatial and binary) were compared by independent t test and participants' responses from the post-experiment survey were compared between groups by an independent t test. If not, the non-parametric 2- group Mann-Whitney U Test regarding Subjective riskiness and Subjective control to investigate the subjects' perception of their own riskiness and to find out if the feeling of control had been successfully perceived by participants.

3.2.1.5.2 Calculating Hit Rates

In this experiment participants received veridical feedback about their performance and we sought to understand the relationship between task success, feedback and risk propensity. We reasoned that smaller targets would be harder to hit than larger targets (Tresilian, 2012; Tresilian, Oliver, & Carroll, 2003) and that the provision of spatial and binary feedback would modulate success rates. Specifically, we expected that the Spatial group would, through additional feedback about how to correct performance errors, learn more about the task and this would ultimately lead to higher hit rates relative to the Binary condition.

To examine this, participants mean hit rates for different target size conditions were calculated and data points were fitted using a linear model for each feedback condition. Then, the two linear models were compared by using the pairwise comparison *emtrend* function in the *emmeans* package in R. The *emmeans* package is used to acquire estimated marginal means for various models such as generalized linear models, models for counts, multivariate, multinomial, and ordinary responses (Lenth, Singmann, Love, Buerkne, & Herve, 2019). The *emtrend* allows one to compare two fitted models to one continuous predictor interaction with a categorical predictor (Lenth et al., 2019).

To investigate the correlation between the riskiness and performance, target size was grouped according to pixel size (20- 30; 31- 41; 42-52; 53-63; 64-74 and, 75- 85 pixels; please refer to the apparatus to convert from pixels to cm). Then we averaged the hit rate based on these categories for each participant to generate z scores for each category per participant. Then we averaged the z scores within each participant to have a unique score for each participant. After that, participants' risk scores were compared with participants hit rate by using the Spearman rank correlation as assumptions of normality were violated.

3.2.1.5.3 Quantifying Risk Propensity

The primary dependent variable in this study was participants risk propensity. On each trial, a participants' selection could either be risky or safe. If participants selected the target with smaller width than the other target width on a given trial, their response was considered as risky, otherwise the responses to the given trials were considered as the safety target. The mean of the participant riskiness is calculated by sum of risky choices divided by trial number which was used for analyses. Riskiness varied from 1 to 0, where 1 is risky and 0 is safe and neutral choice would be 0.5.

The groups were tested in terms of normality by Shapiro-Wilk Normality test and the equality of variance. If these assumptions had not been violated, the difference of risk propensity between groups (spatial and binary) was compared between groups by independent t test. If not, the non-parametric 2- group Mann-Whitney U Test was deployed.

3.2.1.5.4 Switch Analyses

To investigate whether participants were sensitive to outcomes on trials and how this feedback might influence choice strategy, we performed a 2 (feedback; spatial and binary) X 2 (previous selection; risky, safe) X 2 (outcome; miss and hit) mixed ANOVA.

3.2.1.5.5 Error Correction

To understand how much participants corrected their movements in response to the externally presented feedback, we calculated a measure of error correction. Data for error correction was derived by subtracting the spatial error shown on the previous trial (both hit and miss) from the spatial error on the subsequent trial. We reasoned that error correction in the binary feedback condition would be driven by intrinsic information whilst participants in the Spatial condition could see use the externally presented information to make their corrections. Data points were fitted using a linear model through the lm function in R for each feedback condition. A very steep slope would indicate that participants made larger corrections for the error on the previous trial. The two linear models were then compared using the pairwise comparisons *emtrend* function in *emmeans* package.

The *ezANOVA* package in R was used to run the analysis of variance. Bonferroni corrections was used applied to all post-hoc comparisons.

3.2.2 Results

3.2.2.1 Preliminary Analysis

The comparison of participants' age in the Binary feedback condition (M=20.38, SD=4.25) and participants' age in the Spatial condition (M=20.92, SD=2.85) showed no significant difference between the two groups (t(22)=-0.29, p = 0.774).

The subjective risk scores for binary feedback (W=0.87589, p= 0.06276) and spatial feedback (W=0.92836, p = 0.3631) did not violate the normality assumption. There was no significant difference between the variances of the two sets of data [F(11,12) = 1.2924, p = 0.678]. There were no differences in subjective risk (M = 4.69, SD= 1.84, SE= 0.51 for binary; M = 4.58, SD= 1.62, SE= 0.47 for spatial) between the two groups (t(23) = 0.15639, p = 0.877).

The subjective control scores for binary feedback (W= 0.72016, p = 0.001) and spatial feedback (W= 0.93911, p = 0.487) did not violate the normality assumption. There was no significant difference between the variances of the two sets of data [F(11,12) = 0. 73151, p = 0.5982]. The independent t test was computed and there were no differences in subjective control (M = 4.23, SD= 0.93, SE= 0.26 for binary; M = 3.92, SD= 1.08, SE= 0.31 for spatial) between the two groups (t(23) = 0.78083, p = 0.4429). Since the normality of samples assumption for the parametric test was violated, a non-parametric 2- group Mann-Whitney U Test was also conducted for subjective control scores between the two groups, but the result showed that the differences between groups were equal to zero (W = 93. p = 0.4086).

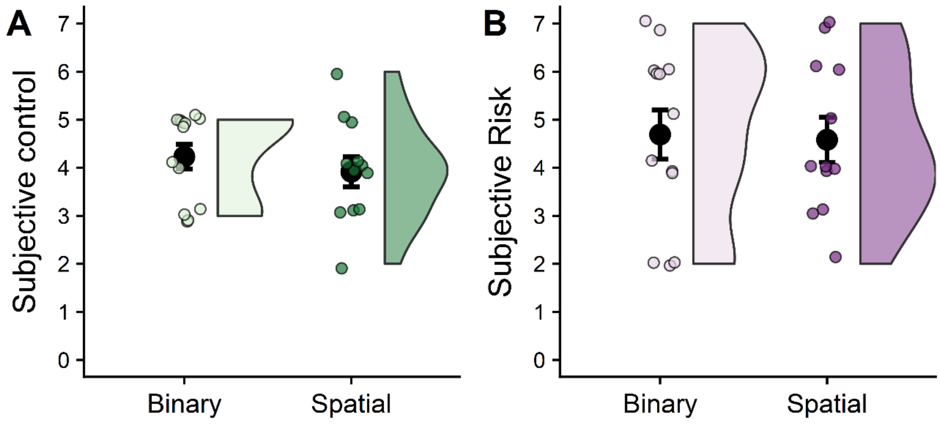

Figure 3.1 Subjective ratings of control and riskiness as a function feedback. A) Participants rated if they felt in control of the outcome of the task. There was no significant difference between each group regarding subjective control as expected. B) Participants rated how risky they thought they were in each session. The subjective perception of their own selection is also aligned with the subjective control ratings. There was no significant difference between each group regarding subjective riskiness. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

To summarise, participants' age did not vary between groups. The subjective control results indicated that both groups felt control to similar degrees (Figure 3.1A). The subjective riskiness results indicated that levels of risk seeking behaviour for both groups were similar (Figure 3.1B).

3.2.2.2 Primary Analyses

3.2.2.2.1 Hit Rate Analyses

To investigate the relationship between participant performance (hit rate) and target size for both spatial and binary feedback condition, the mean hit rate for each target size was taken for each participant. The linear models from the two groups were represented in Table 2. The linear model for binary feedback showed a smaller value for slope suggesting that the hit rate changes marginally as a function of target size compared with spatial feedback. On the other hand, the linear model for spatial feedback suggests that participants had a better hit rate when the target size was larger. The pairwise comparison between the two models showed that these two models were significantly different from each other (t(984) = -3.729, p=0.0002) (Figure 3.2).

Table 2 The results of fitted linear model for each condition.

Feedback type	ß	df	Lower confidence level interval	Upper confidence level interval
Binary	0.002	984	0.001	0.004
Spatial	0.006	984	0.005	0.007

We then averaged riskiness score for each participant, where 0 was safest and 1 was riskiest, based on their selection. These riskiness scores failed the normality test (W = 0.88013, p = 0.00695); therefore, the Spearman rank correlation was conducted to investigate the relationship between participant hit rate and riskiness score. There was a significant correlation (r(25) = .407, p = 0.043), indicating that participants’ risk seeking increased when participants' performance increased.

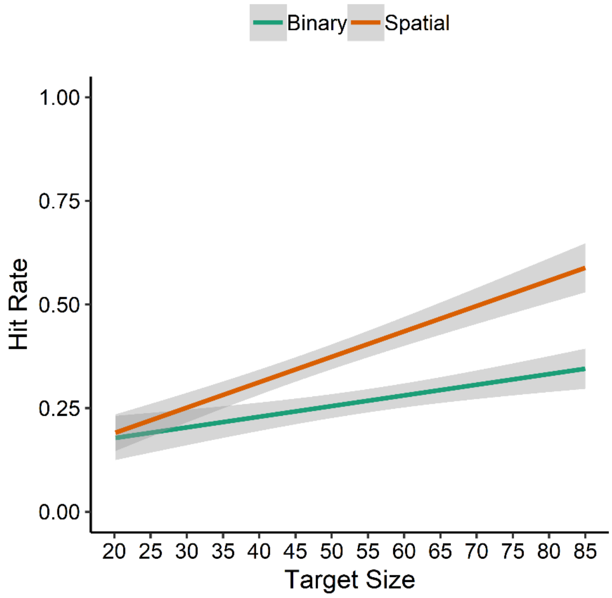

Figure 3.2 Linear models for spatial and binary feedback groups. The spatial feedback model suggests that the hit rate increases based on the target size more than binary feedback model. The models are significantly different than each other. The longest target size/width is 85 pixels and the shortest target size/width is 20 pixels. The models were generated using the lm function in R.

3.2.2.2.2 Riskiness Analyses

Our hypothesis was that the amount of information presented in movement feedback would affect risk taking behaviour. Whilst the pattern of decision strategies ranged only from the risk-neutral to risk-averse, there was a marked difference in target preference with participants in the Binary condition consistently preferring to select the targets with the largest width (safest options) (Figure 3.3 A&B).

The normality assumption of mean of riskiness for spatial feedback was not violated ($W=0.91106$, $p = 0.2201$); for binary feedback was violated ($W= 0.75978$, $p = 0.0023$). There was no significant difference between the variances of the two sets of data [$F(11,12) = 0.929$, $p = 0.896$]; therefore, an independent t-test was computed. This showed significant differences in riskiness between two groups ($t(23) = -4.094$, $p < 0.001$); however, the nonparametric Mann-Whitney U Test was also conducted because of failing normality test of riskiness in the binary feedback condition. The result also showed a significant difference (W = 21, $p = 0.002$). Averaged across trials, the binary feedback condition (M=0.15, SD=0.19, SE=0.05) showed more risk averse behaviour than the spatial feedback condition (M=0.47, SD=0.20, SE= 0.06) (Figure 3.3D). This pattern remained consistent over time, with participants adopting similar strategies on both cycles of trial presentation.

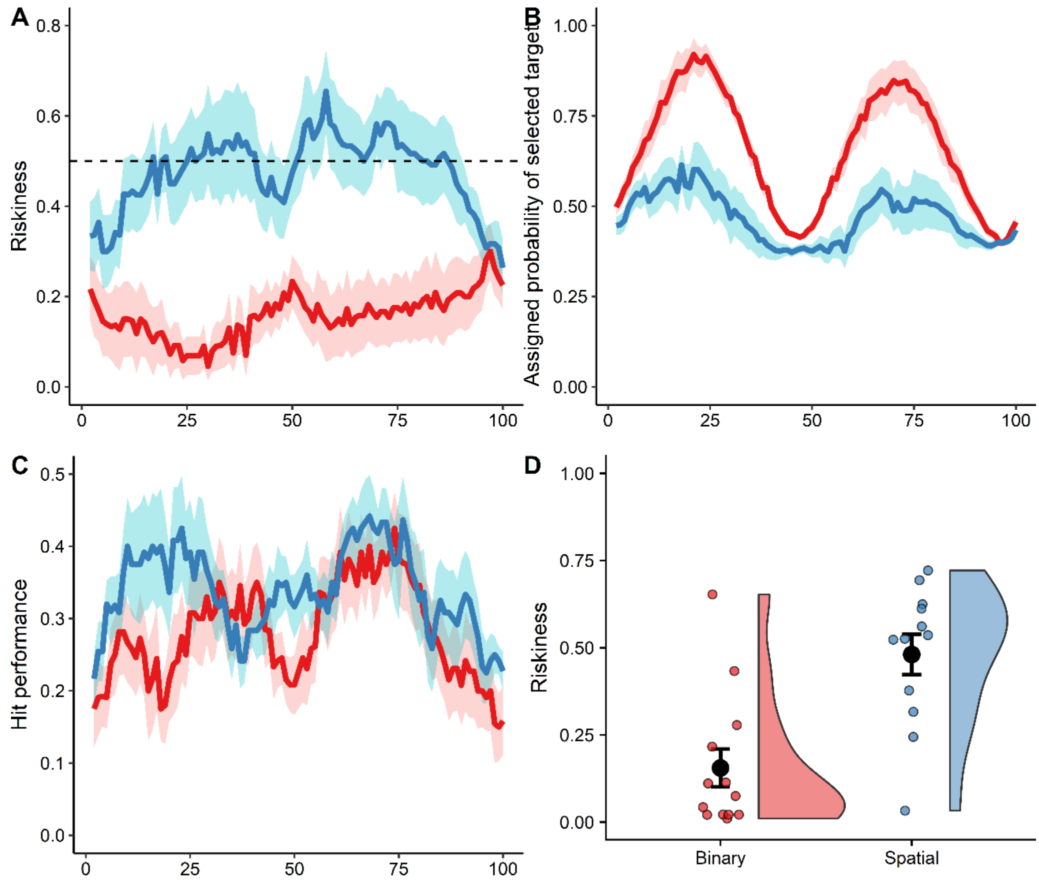

Figure 3.3 Risk Propensity and Hit Rate as a fucntion of feedback. A) Moving averages of participants' risky selections from binary values where 1 is risky and 0 is safe. The two lines represent spatial (blue) and binary (red) groups across time (from trial 1 to trial 100). Participants in the Spatial condition adopted more risk-seeking behaviour relative to participants in the Binary condition throughout the experiment. The black dotted line indicates neutral behaviour. B) Participant selection of the probability of target represented as moving average. The participants in the Spatial condition are selected targets with risky probabilities more than participants in the Binary condition. C) Hit performance for both groups was generally low, however, the hit performance of participants in the Spatial condition remained relatively constant throughout the experiment, whereas, participants' performance in the Binary condition increases towards the end. Towards the end of the experiment, even if participants perform more or less similar, there appears to be a confound due to change in target size. D) Mean of riskiness of each group. It is clear that participants in the Spatial condition were more risk-seeking than participants in the Binary condition. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

3.2.2.2.3 Error Correction Analyses

To investigate the participants' performance, we also took the error correction into consideration. The linear models from the two groups are represented in Table 3.

Table 3 The results of fitted linear model for each group.

Feedback type	ß	df	Lower confidence level interval	Upper confidence level interval
Binary	-0.364	2336	-0.404	-0.324
Spatial	-0.921	2336	-0.983	-0.858

The linear model for binary feedback shows a small value for slope suggesting that the model is skewed from the idealised error correction model. On the other hand, the linear model for spatial feedback was closer to the ideal error correction model. The pairwise comparison between the two models showed that these two models were significantly different from each other ($t\ (2336) = 14.622$, $p < .0001$) (Figure 3.4). The result indicated that participants in the Spatial group used the feedback from spatial error to inform their behaviour on subsequent trials and this degree of correction was greater than that in the Binary group.

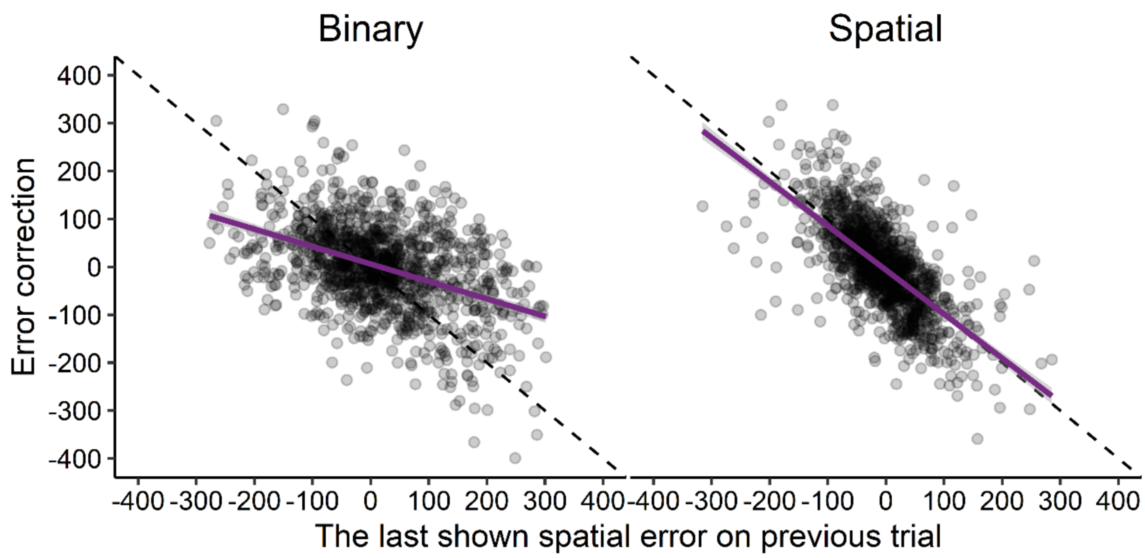

Figure 3.4 Error correction based on previous feedback. On the x axis, the value of last seen spatial error (mm) on previous trial. On the y axis, the differences between their last seen spatial error value and their current spatial error value (mm). An ideal person who would correct the error accordingly has been shown as dotted line in the graphs. In the graph participants purple line in the Spatial group shows that the linear model of participants' correction approaches the ideal error correction. However, the linear model in the Binary group does not present a well-adjusted error correction. The correction in the Binary group should be intrinsic error correction based on the knowledge of result, whereas, participants in the Spatial condition actually see the spatial feedback in every trial. Each data point shows an individual trial.

3.2.2.2.4 Switch Analyses

The final analysis of these data investigated whether people switched decisions from risky option to safe option and vice versa, after they had a miss or a hit depending upon the feedback type. A 2 (feedback type; binary, spatial) by 2 (outcome; miss, hit) by 2 (previous selection; risky, safe) mixed design ANOVA was conducted. There was a main effect of previous selection [$F(1,18) = 20.84$, $p < .0001$, $\eta_G^2 = 0.363$]. There was also an interaction between feedback type and previous selection [$F(1,18) = 16.587$, $p < .0001$, $\eta_G^2 = 0.312$] and between outcome and previous selection [$F(1,18) = 34.542$, $p < .0001$, $\eta_G^2 = 0.108$]. Participants tended to switch their selection more if their previous selection had been risky (M=0.52, SD=0.31, SE= 0.05) rather than safe (M=0.22, SD=0.17, SE=0.03). In terms of feedback and previous selection interaction, simple effect analyses were conducted. First the data was split based on previous selection as risky and safe and the difference between feedback types was analysed using a pairwise t test with Bonferroni correction. Participants in the Binary group switched more after a risky choice than participants in the Spatial group ($p<0.001$). In other words, participants in the spatial feedback group were more likely to stick to their risky selection. As expected, participants in the Binary group switched less after a safe choice than participants in the Spatial group ($p<0.001$); however, switch rate in the Spatial group remained similar after both risky and safe selection ($p= 0.32$) (Figure 3.5 A&B).

Secondly, the data was split based on previous selection as risky and safe and the difference between outcomes was analysed using a pairwise t-test with Bonferroni correction. After a safe decision, participants were likely to switch the selection when they missed more than they hit ($p= 0.045$). Participants' switch rate after a hit was higher when their previous selection was risky rather than when their previous selection was safe ($p<0.001$). After a miss, participants were more likely to switch the selection if their previous selection was risky rather than if their previous selection was safe ($p= 0.054$) (Figure 3.5C &D).However, the marginal difference should be regarded as non-significant as the criteria of alpha threshold is considered $p<0.5$ in this thesis.

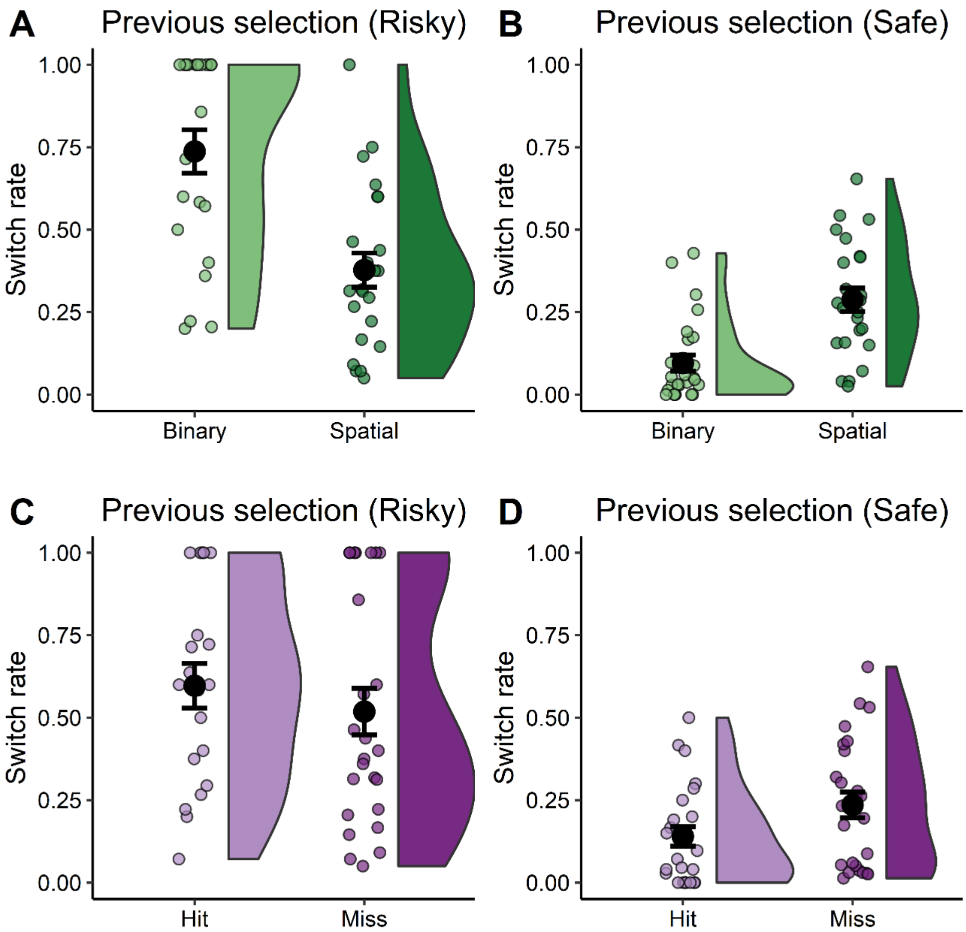

Figure 3.5 Switch Rates as a Function of Previous Choice. A) Participants were more likely to switch their selection after a risky choice in the Binary group compared to the Spatial group. B) As might be expected participants were also more likely to switch their selection after a safe choice in the Spatial group compared to the Binary group. When there was more information about their own motor execution, they were more likely to switch to risky selection. C) Participants were more likely to switch after a risky choice, however, D) After a safe choice, participants more likely to switch if they missed and they were more likely to stick their safe decision after a hit. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

To sum up, the Spatial feedback condition resulted in a higher hit rate and higher risk-seeking behaviour. Participants in the spatial feedback group adopted a well-adjusted error correction, significantly different to the binary feedback group. Spatial feedback resulted in fewer switches after a risky decision whereas, the switch rate after a risky selection was significantly higher for the Binary group. Switch rate after a miss or hit was modulated by previous selection. The previous risky selection resulted in higher switch rate for both miss and hit. When the previous selection was safe, the switch rate was high for a miss more than a hit. In other words, people who missed in the safe selection tended to switch more compared to people who hit in safe selection.

3.2.3 Discussion

Consistent with the hypotheses, it was found that increasing information on feedback has an impact on risk appetite. Specifically, spatial feedback is correlated to higher hit rates and results in higher risk seeking behaviour when making discrete decisions. It is worth noting that although there are differences in nomenclature, the feedback conditions constitute classic feedback manipulations of knowledge of results and knowledge of performance- long known to have differential effects in the learning of a skilled motor activity. The latter provides more information to the learner (Gentile, 1972) and therefore, it was reasoned that participants provided with this feedback would be able to more readily optimize and thus be biased towards selecting riskier options in an attempt to maximize reward, relative to the binary feedback condition.

A key finding from these results is the degree of error correction exhibited by each group. Participants in the spatial feedback condition made more corrections than participants in the binary feedback condition. This may be related to the information provided to both conditions; the information on how to correct the error is more effective than just being informed of an error (Kernodle & Carlton, 1992). The details of performance were externally available for spatial feedback; however, the participants in the Binary feedback did not have any external information about the error. Accordingly, they did not know externally how to correct the error. Since the error was not explicitly given in the Binary feedback, participants needed to rely on their own sensory perceptual information that was accessible as a consequence of movement being enacted (van Vliet & Wulf, 2006); therefore, those in the binary feedback condition had to rely on intrinsic feedback. Hence, any correction would be the result of proprioceptive information; therefore, they presumably made worse corrections which might also explain why they had a worse hit rate than participants in the Spatial feedback condition.

In contrast to the findings in Chapter 2, risk propensity was significantly different between the two different feedback types. Participants in the binary feedback condition showed a biased selection towards being risk averse whereas participants in the Spatial condition seemed to be neutral. A possible explanation for this might be that when a failure is attributed to motor execution, reinforcement learning might be adjusted (McDougle et al., 2016). Receiving feedback on the agent's own performance might relate to assigning the credit to agency rather than external factors (McDougle et al., 2016; Parvin et al., 2018). Less information about motor execution might not result in learning, which then causes a selection bias.

Rewards were linked to the target difficulty but hit probability could not be controlled; as such, the participants' own motor competence determined the likelihood of reward. The results showed that success rates varied as a function of target size and, as expected, there was superior performance in the spatial feedback condition with marginally higher hit probabilities across targets. Another interesting finding was that participants in the spatial feedback condition showed better performance than the participants in the binary feedback condition, after controlling for the target size. This might confirm one of the expectations that more information would result in better performance (Wulf et al., 2010), in this case a better hit rate. Consequently, when people exhibited better performance, they were more likely to be risk seeking in a task where the aim was to score as many points as possible. The reason why individuals in these circumstances may take more risks is that a better hit rate means less error representation. In this score driven task, people would aim to reach as many points as possible. Those who achieve more hits might actually then select a target which gives higher points. The target with the higher expected value- would be an optimal choice to select. It is known that individuals are prone to behave optimally when they execute an action (Neyedli & Welsh, 2014; Trommershäuser et al., 2008). Naturally, people would be driven to be more risk seeking because the expected value would be higher for risky targets for those receiving spatial feedback, due to their higher hit rate. Consequently, a better hit rate might result in risky decisions, which, in this study, meant participants in the spatial feedback condition showed more risk-seeking behaviour than participants in the binary feedback condition. These findings raise intriguing questions regarding the nature and extent of expected value (EV). One of the issues that emerges from these findings is the unequal EV value for target pairs. EV varies between participants depending on their hit rates; therefore, EV is not equivalent, which might pose some limitations. To develop a full picture of this manipulation, additional studies will be needed, where the probability of hitting, and therefore the hit rate, is not the result of performance but is in fact fixed.

In conclusion, providing information about the execution error resulted in increased risk-seeking behaviour; however, this might have been contaminated by the variability of performance. Different EV might drive risk seeking behaviour; therefore, there is a need for an experiment in which the EV can be controlled.

3.3 Experiment 3

The previous study indicated that there was a change in risk propensity for those who received execution error information. Differences in motor performance (hit rate) would result in individuals having different expected values for the same targets. Motor control tasks are sensitive both to the reward values and the probability of success (Wolpert & Landy, 2012).

It is understood that people performing motor control tasks tend to make more optimal selections than those who perform selection tasks that do not require motor execution in the task (Neyedli & Welsh, 2013, 2014; Trommershäuser et al., 2005; Trommershäuser, Maloney, & Landy, 2003c). To avoid the effect of different EV, the hit rate, which is the only parameter related to participants' performance, needs to be fixed. The idea of fixed hit rate has been used in previous studies to equalise EV for each target by giving predetermined feedback (McDougle et al., 2016; Parvin et al., 2018). In the current study, predetermined feedback will be used too, which is independent of performance, which enables EV to be kept constant. Uniquely in the current study the EV will be kept constant throughout the experiment by fixing hit rate which is independent of performance.

The aim of the current study is to investigate the effect of knowledge of the execution error has on risk propensity. The feedback provided will differ in the information provided as in the previous experiment. It is expected that receiving information on performance (for those in the spatial feedback condition) would make people assign greater credit to themselves for the motor execution, than those receiving only information on the result (the binary feedback condition). Consequently, participants in the spatial feedback condition are more likely to be risk seekers than participants in the binary feedback condition. Meanwhile, the expected value for each target, and of the target pairs, will remain constant by delivering predetermined feedback; however, predetermined feedback might result in a difference between the participants' expectations of their own performance, and the predetermined feedback they receive (reward schedule).

3.3.1 Methodology

3.3.1.1 Sample

Sixty-three people (aged 17 to 30 years; M=18.51, SD=2.25; 38 Female) visiting the School of Dentistry at the University of Leeds, Dentistry were recruited for this study. The Edinburgh Handedness Inventory (EHI) was used to assess participants handedness (Oldfield, 1971). Three people were classified as left handed (EHI < -40), 15 ambidextrous (-40< EHI<40) and 45 people were right handed (EHI > 40). All participants reported normal or corrected-to-normal vision. Approval was obtained from the local research ethics committee (Reference 271016/MM/216).

3.3.1.2 Task

In this study, the interceptive timing task reported in Experiment 2 was used, however, in this version, outcome feedback was predetermined and participants received pseudo-feedback based on a predetermined reward schedule and fixed based on target size (Figure 3.6)

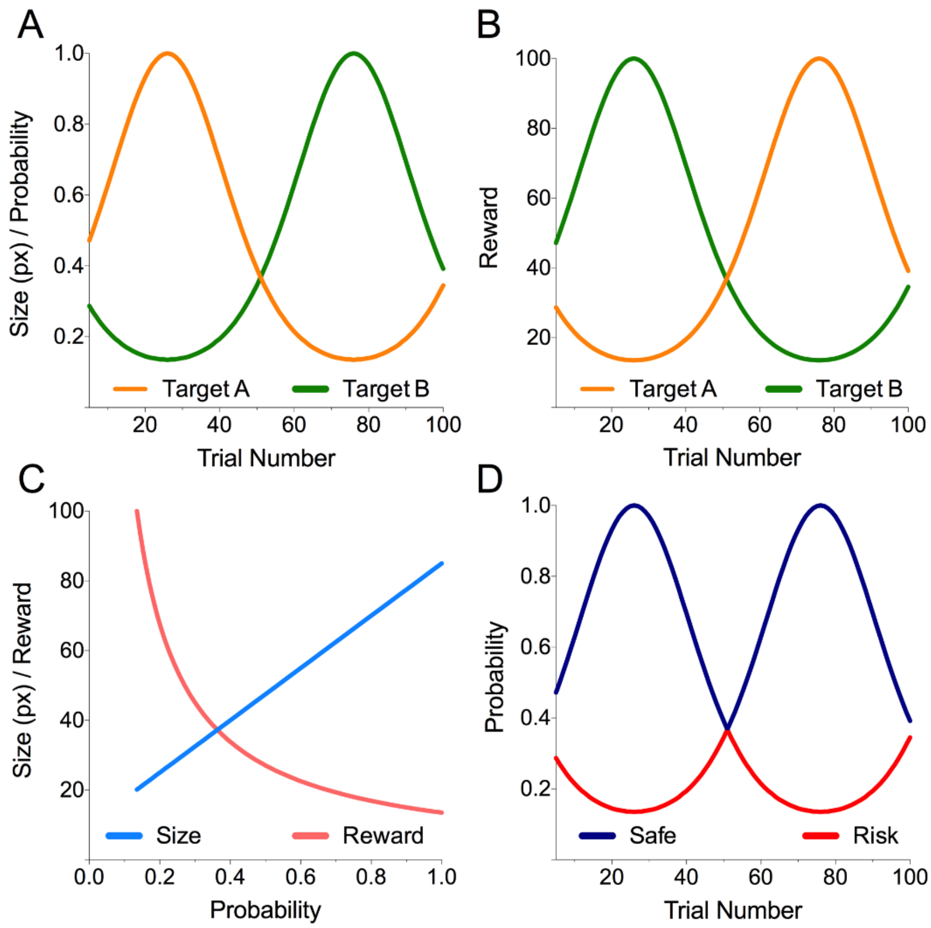

Figure 3.6 Decision-Making Task Properties. (A) In the current study, participants selected between targets of varying widths with corresponding hit probabilities predetermined across 100 trials; (B) Selecting and hitting smaller targets produced larger rewards relative to selecting larger targets; The relationship between target size in pixels and reward is presented in panel (C). (D) The magnitude of the riskiness of the decision (difference between the small and large target) varied across the task and the target associated with the riskier options reversed once.

Hit probability and reward functions were manipulated according to target size, such that the EV was matched in every trial and kept constant throughout the experiment. The participant received the associated reward value on hit trials. (Please see 2.3.2.1 Reward Schedule for details). In this study, target pairs were represented in the same order for every participant (Figure 3.6A, B & C).

3.3.1.3 Study Design

A between subject study design was employed. Participants were assigned to two different groups; Binary feedback condition and Spatial feedback condition.

3.3.1.3.1 Subjective Measure

Participants were asked to complete the same post-experiment survey at the end of each condition. The survey (using a 7-point Likert scale) required participants to state the extent to which they agreed with the following three statements: “I felt in control of the outcome of the task”;” I was risk-seeking during the task”; and “The game tracked my movements accurately”.

3.3.1.4 Statistical Analysis

Because of the similar study design to Chapter 3.2 (Experiment 2), the same statistical analyses were conducted in the current study.

3.3.2 Results

3.3.2.1 Preliminary Analysis

Participants' age in the binary (M=18.59, SD=2.55) and spatial (M=18.42, SD=1.93) feedback conditions were compared and the result shows that there is no significant different between the two groups ($t(57.63) = 0.31$, $p = 0.760$).

The normality was tested for spatial feedback subjective risk scores (W=0.88529, p = 0.003) and for binary feedback subjective risk scores (W= 0.95061, p = 0.149). The sample of variance for both feedback conditions was not violated [$F(30,31) = 0.72453$, $p = 0.377$]. The independent t test was computed and there were no differences between subjective risk (M = 3.75, SD= 1.44, SE= 0.25 for binary; M = 3.87, SD= 1.69, SE= 0.30 for spatial) between two groups ($t(61) = -0.30664$, $p = 0.760$). Since the parametric tests assumes the normality of samples was violated, a non-parametric 2- group Mann-Whitney U Test was also conducted for subjective risk scores between the two groups, but the result showed that the differences between groups were equal to zero (W = 495. p = 0.994). The normality was tested for spatial feedback subjective control scores (W= 0.93425, p = 0.057) and binary subjective control scores (W= 0.91819, p = 0.018). The sample of variance for both groups was not violated [$F(30,31) = 0.49494$, $p = 0.055$]. There was no difference in subjective control (M = 3.31, SD= 1.20, SE= 0.21 for binary; M = 3.52, SD= 1.71, SE= 0.31 for spatial) between the two groups ($t(61) = -0.54801$, $p = 0.585$). Since the parametric tests assume the normality of samples was violated, a non-parametric 2- group Mann-Whitney U Test was also conducted for subjective control scores between the two groups but the result showed that the differences between groups were equal to zero (W = 475. p = 0.773).

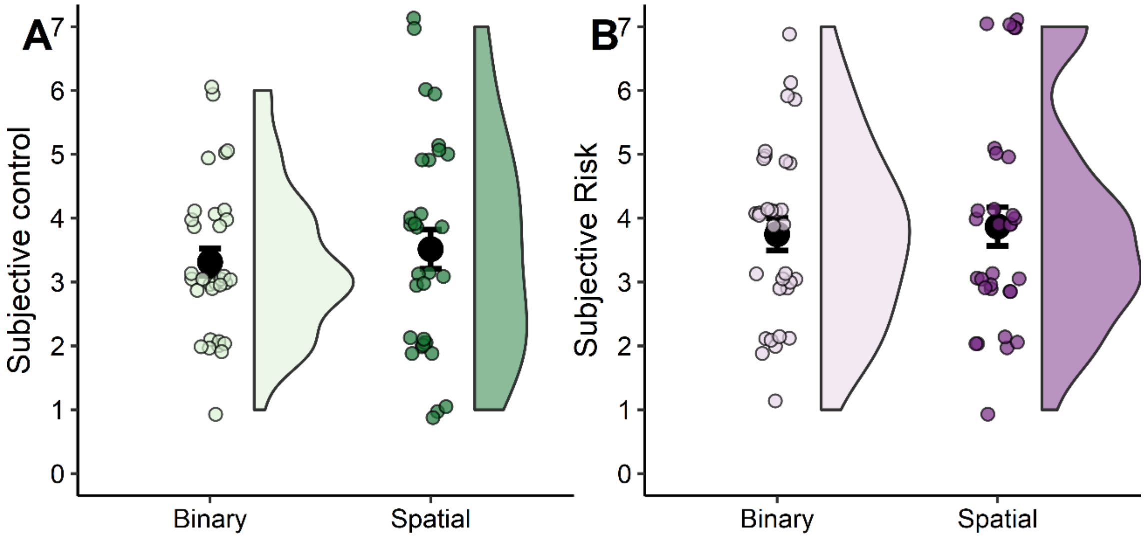

Figure 3.7 Responses from post questionnaire for each feedback type. A) Participants rated if they feel in control of the outcome of the task. There is no significant differences between each group regarding subjective control B) Participant rated how risky they think they are in each session. The subjective perception of their own selection is also aligned with the subjective control ratings. There was no significant differences between each group regarding subjective riskiness. The data point shows the participants' rating and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

To sum up, participants' age did not vary between groups. The subjective control results indicated that both groups felt control to a similar degree (Figure 3.7A). The subjective riskiness results indicated that both groups were risk takers to a similar degree (Figure 3.7B).

3.3.2.2 Primary Analyses

3.3.2.2.1 Riskiness Analyses

In the previous study, our hypothesis was that the amount of information presented at movement feedback would affect risk taking behaviour. In this study, we investigated whether the effect remains when we control motor performance.

Whilst the pattern of decision strategies ranged only from risk-neutral to risk-seeking, there was a marked difference in target preference with participants in the spatial feedback condition consistently preferring to select the targets with the smallest width/safe options (Figure 3.8A &B). The normality was tested for spatial feedback risk scores ($W=0.93086$, $p = 0.051$) and for binary feedback risk scores ($W= 0.97618$, $p = 0.717$). There was no significant difference between the variances of the two sets of data [$F(29,29) = 0.78383$, $p = 0.516$]. There was significant differences in riskiness between the two groups ($t(58) = -2.5524$, $p = 0.013$). Averaged across trials, the binary feedback condition ($M=0.56$, $SD=0.14$, $SE=0.03$) showed statistically significantly less risk seeking behaviour than the spatial feedback condition ($M=0.66$, $SD=0.16$, $SE=0.03$). This pattern remained consistent over time, with participants adopting similar strategies on both cycles of trial presentation.

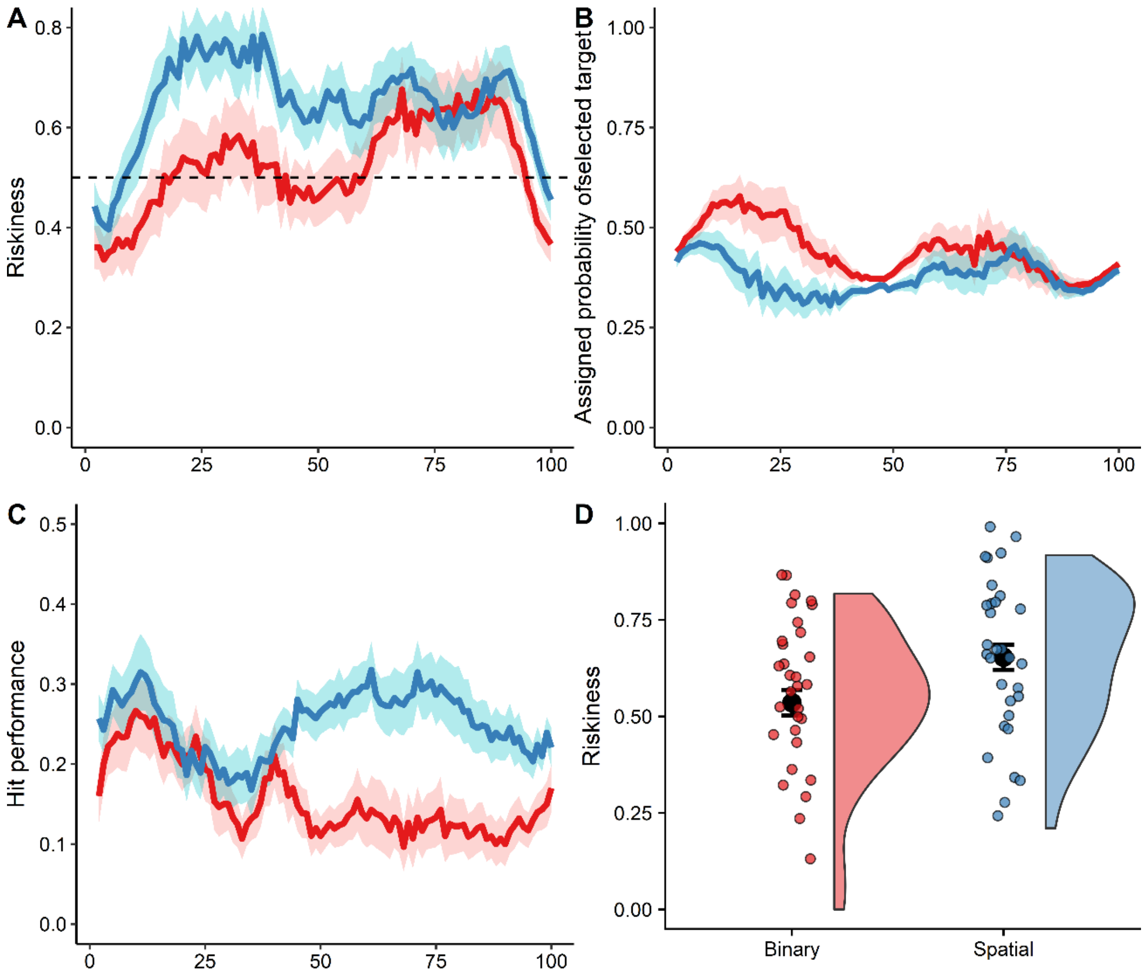

Figure 3.8 Differences in risk propensity and hit rate as a function of feedback. A) Moving average of participants' risky selections from binary values where 1 is risky and 0 is safe. Participants in the Spatial condition (blue) adopted more risk-seeking behaviour compared to participants in the Binary condition throughout the experiment (from trial 1 to trial 100). Risk neutral behaviour is represented by the black dotted line. B) Participants selection of the probability of target is represented as a moving average graph. The participants in the Spatial condition are selected targets with risky probabilities more than participants in the Binary condition which supports the evidence from A&D. C) The graph represent the actual hit performance between two groups, which is quite low for both groups. However, the hit performance of participants in the Spatial condition remains relatively constant throughout experiment, whereas participants' performance in the Binary condition decreases towards the end. Towards the end of experiment, even if participants perform more or less similar, we know that is cofounded by selected target size between two groups. D) The graph represents the mean of riskiness between two groups. It is clear that participants in the Spatial condition were risk-seeking than participants in the Binary condition. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

3.3.2.2.2 Error Correction Analyses

To investigate motor performance, we looked at the degree of error correction participants displayed following each trial per condition. The linear models from two groups were represented in the Table 4. The linear model for binary feedback showed a small value for slope suggesting that the model is skewed from the idealised error correction model. On the other hand, the linear model for spatial feedback was close to the ideal error correction model. The pairwise comparison between the two models showed that these two models were significantly different from each other ($t(5843) = 25.438$, $p<.0001$) (Figure 3.9). The results showed that participants in the Spatial group used the feedback from spatial error and they behaved accordingly in the next trial. Participants in the Binary group only had knowledge of result and presumably they used proprioceptive feedback.

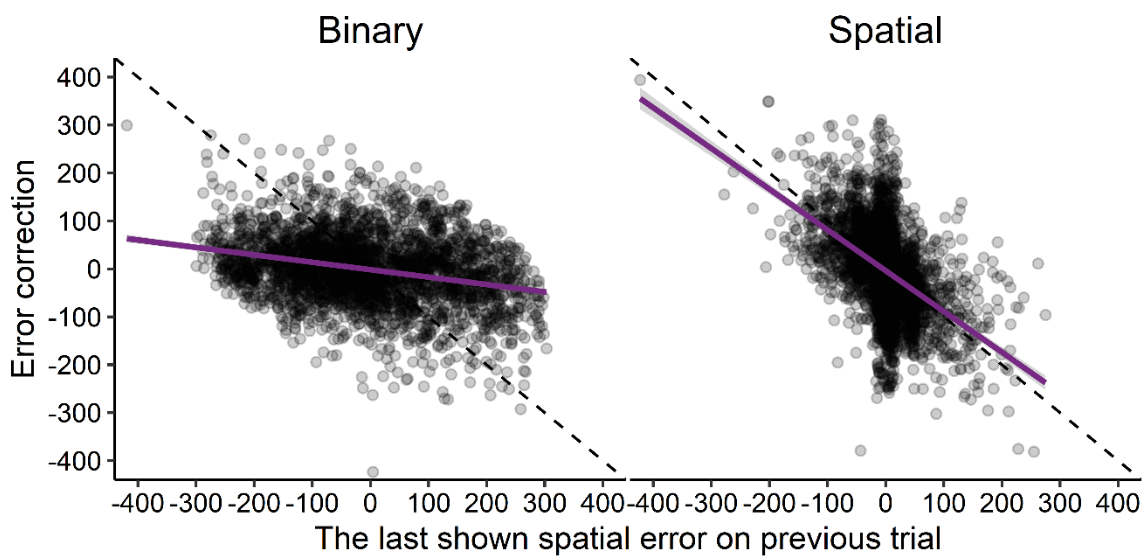

Figure 3.9 Error correction based on previous feedback. On the x axis, the value of last seen spatial error value (mm) on the previous trial. On the y axis, the differences between their last seen spatial error value and their current spatial error value (mm). An ideal person who would correct the error accordingly has been shown as dotted line in the graphs. In the graph participants purple line in the Spatial group shows that the linear model of participants' correction approaches the ideal error correction. However, the linear model in the Binary group does not present a well-adjusted error correction. The correction in the Binary group should be intrinsic error correction based on the knowledge of result, whereas, participants in the Spatial condition actually see the spatial feedback in every trial. Each data points shows an individual trial.

Table 4 The results of fitted linear model for each group.

Feedback type	ß	df	Lower confidence level interval	Upper confidence level interval
Binary	-0.155	5843	-0.176	-0.134
Spatial	-0.850	5843	-0.899	-0.801

3.3.2.2.3 Switch Analyses

The final analysis investigated whether people switched decision from a risky option to a safe option and vice versa when they had a miss or a hit. A 2 (feedback type; binary, spatial) by 2 (outcome; miss, hit) by 2 (previous selection; risky, safe) mixed design ANOVA was conducted. There was a main effect of previous selection [$F(1,60) = 17.240$, $p < .0001$, $\eta^2_G = 0.0961$] and outcome [$F(1,60) = 18.359$, $p < .0001$, $\eta^2_G = 0.0392$]. There was also an interaction between feedback type and previous selection [$F(1,60) = 6.795$, $p = .0115$, $\eta^2_G = 0.0402$]. Feedback and previous selection interaction was investigated by conducting simple effect analyses. First the data was split based on previous selection as risky and safe and the difference between feedback types was analysed by a pairwise t test with Bonferroni correction. Participants in the Spatial group switched more after a safe choice than participants in the Binary group ($p = 0.004$). In other words, participants in the spatial feedback group were more risk seeking after a safe choice than participants in the binary feedback. As expected, participants in the Spatial group switched less after a risky choice than a safe choice ($p<0.001$); however, switch rate in the Binary feedback remained similar after both risky and safe selection ($p= 0.18$) (Figure 3.10A&B). Participants were more likely to switch after a miss (M=0.29, SD=0.18, SE=0.02) than a hit (M=0.22, SD=0.18, SE=0.02) (Figure 3.10C). Participants tended to switch their selection more after a safe decision (M=0.31, SD=0.20, SE=0.02) than risky decision (M=0.20, SD=0.14, SE=0.01) (Figure 3.10D).

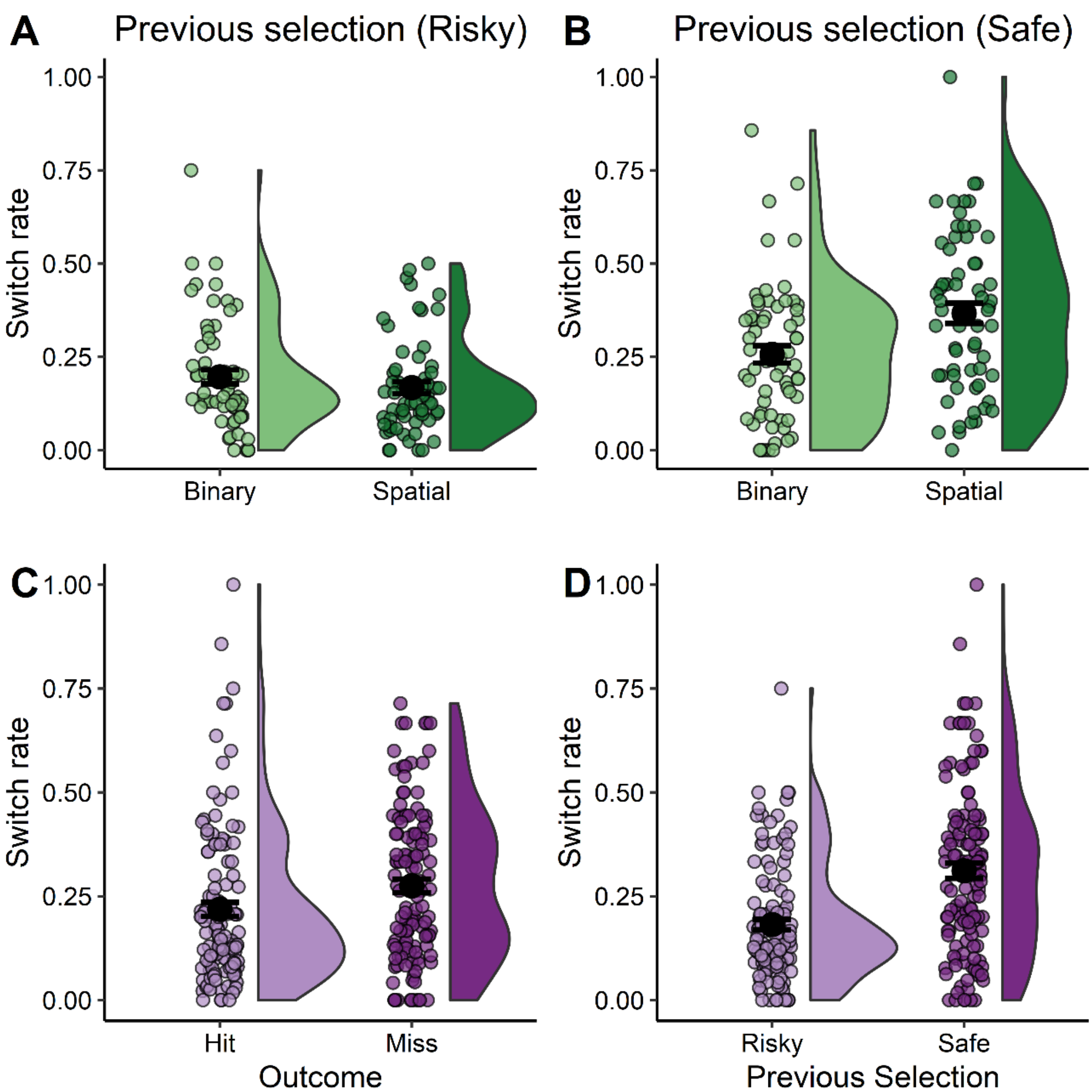

Figure 3.10 Switch rate of participants based on the previous selection. The x axis shows feedback type in A & B. The x axis in C shows the outcome. The x axis in D shows the previous selection. A) In the Spatial condition after a risky choice people are less likely to switch whereas, switch rate is relatively varied after a safe choice. People stick to their choice after a risky choice more than after a safe choice in the Spatial group. B) Participants were more likely not to switch the selection after a hit outcome, which is what we would expect. C) Participants were more likely not to switch the selection after a risky selection. The data point shows the individual means and the black circle represents the group mean. The error bars represent the standard error.

In summary, participants in the spatial feedback condition adopted a well-adjusted error correction, which was significantly different from the binary feedback condition. Spatial feedback resulted in less switches after a risky decision than a safe decision. Spatial feedback led to more switches after a risky decision compared to binary feedback too. Switch rate after a risky or safe selection was modulated by feedback type. The previous risky selection and hit outcome resulted in lower switch rate.

3.3.3 Discussion

The present study sought to investigate differences in risk seeking behaviour between those receiving different feedback types, where motor actions were involved in a decision making task. Consistent with our hypotheses, we found that increasing the information contained in the feedback, particularly receiving execution error (performance error) would have an effect on the decision, in terms of its riskiness. Hereafter the potential functional meaning of these results is discussed in more detail.

Firstly, in this study, the feedback type was found to change the risk propensity. Participants in the spatial feedback condition were more risk seeking than participants in the binary feedback condition. This result was as would be expected from the work of McDougle et al. (2016), where receiving information on motor execution error led to participants adopting greater risk seeking behaviour, choosing targets with a lower probability of hitting.

In contrast to findings in Chapter 2, risk propensity was significantly different between the two different feedback types. Participants showed a biased selection, based on the error information they received about their execution. A possible explanation for this might be that when a failure is related to motor execution, reinforcement learning might be adjusted (McDougle et al., 2016). Receiving more information about motor execution might result in learning, which then causes a selection bias towards future risk seeking behaviour. In Chapter 2 the manipulation was mainly on the way to execute the decision, examining the internal factors of the sense of agency; however, in the current study, we kept the execution method for the decision constant and manipulated just the external information, which might be related to the sense of agency (spatial feedback). Since this can give a chance to control the internal feeling of sense of agency, the manipulation of feedback might have affected the risk propensity.

Another important finding was in the error correction for each group. Participants in the spatial feedback condition made corrections much better than participants in the binary feedback condition, which aligns with the result in the previous experiment. Participants in the binary feedback condition only had knowledge of whether they hit or miss the target, and so they had to rely on their intrinsic feedback for information about performance error. Hence, any correction would be proprioceptive. However, participants in the Spatial condition had spatial information as external feedback. Receiving this motor execution error might lead to the participants assigning more credit to themselves for the execution than to external factors (McDougle et al., 2016). In addition, those that received execution error information presumably made better corrections, which can then also explain the observation that they had a better hit rate than participants in the binary feedback condition.

3.3.4 Conclusion

In conclusion, receiving information about the execution error resulted in greater risk-seeking behaviour. This might be because receiving the information on the execution error, might lead people to assign the credit to themselves, and therefore increase their future risk propensity.

The results suggest that receiving execution information leads to increased risk seeking behaviour compared to those who receive only binary information of success or failure. Receiving spatial feedback also results in higher hit rates, which might have contaminated the initial results; therefore, another study was conducted where the hit rate was predetermined for each target. The results of the second study confirmed those of the first that people might be biased towards being risk seeking, when they are given information on their execution error.

The predetermined feedback is different to the participants' own performance so they receive misleading information about their own performance, for instance, they actually perform worse than the performance they are given in the feedback. This might cause them to develop an overrated or underrated belief of their competency; therefore, In the next chapter this will be investigated to determine whether there will be an effect of motor competence on decision making.

Chapter 4 : The Impact of Sensorimotor Competence on Risk Propensity

4.1 Abstract

The previous chapters have examined the effect of feedback on risk propensity. Evidence from the previous chapters in this thesis is accumulating for the idea that that risk seeking might be modulated by the degree of *information* available to an individual. Specifically, it is proposed that agents who obtain more sensorimotor information about the task (and thus greater confidence in the precision of their estimates about gaining reward through interactions with the environment) may be biased towards risk seeking behaviours. This chapter takes an alternative approach to manipulating sensorimotor confidence by asking participants to perform a two-alternative forced choice interceptive decision-making task using their non-preferred hand. We reason that this manipulation should result in increased sensorimotor noise and reduced precision of the reward estimate leading to risk aversion. We test this hypothesis across two studies employing within and between subjects designs. The findings from experiment 4 reveal potentially contradictory results: while using the non-preferred hand, participants in the binary condition became more risk-seeking over time whilst participants in the spatial condition had constant level of riskiness over time. In the experiment 5, participants in the binary condition became less risk-seeking when switching from using non-preferred to the preferred hand. However, participants in the Binary condition seemed to be greater risk seekers compared to participants in the Spatial conditions when they need to switch hand after first block. Meanwhile, spatial feedback consistently resulted in better error correction than binary feedback in both experiments. These findings reveal that there is still much to learn about the interaction between feedback and motor skill and how these factors interplay for risk taking.

4.2 Introduction

Previous literature (McDougle et al., 2016), and the results from Chapter 3 have indicated that manipulating the availability of information about one's motor execution (through presentation of binary and spatial feedback) can modulate risk propensity. We hypothesised that this may be driven by a change in the rate of information available to the agent interacting with the environment, impacting on the *precision* of the estimate of the outcomes of the sensorimotor commands. In other words, when participants interacted with the interceptive decision-making task presented to them, there was an increase in the uncertainty associated with appropriateness of the executed action in the binary feedback condition (where information on action outcome was limited) relative to the spatial. It stands to reason that the more precise one's estimates about the consequences of their actions, the better positioned they are to try to maximise utility. Conversely, if the mapping between action and reward is unclear or constrained (e.g. via limited feedback) then a risk averse strategy seems like a sensible one to adopt until more information has been accumulated and can be exploited.

External feedback provides information that allows one to refine their model of the environment and body, which helps the motor system to select the appropriate action from a repertoire of possibilities (Shadmehr & Mussa-ivaldi, 1994; Thoroughman & Shadmehr, 2000). Internal sensory signals and external feedback combine to indicate the consequences of a motor action. We have seen in the previous experiments that manipulating the quality of externally presented feedback can modulate task performance (and learning) and influence risk propensity. Specifically, we found that providing participants with only information about task success (binary outcomes on success and failures) meant that these participants were unable to correct their spatial errors as much as participants provided with spatial feedback and that participants in this condition showed more risk averse behaviour. When we controlled for task performance by manipulating feedback, we found that this risk aversion persisted in this group.

One possible explanation for this finding is that the limited external information constrains the precision of ones estimates about the consequences of their actions (relying only on proprioceptive signals which are known to drift over time without calibration; Wann & Ibrahim, 1992) and thus increases the amount of time one needs to explore the environment to obtain a sufficiently accurate model of the task that allows them to subsequently exploit. In contrast, external information about execution error provided in the Spatial condition indicated on each trial how far away the participants performance was to (Schmidt & Lee, 2005; van Vliet & Wulf, 2006; Weeks & Kordus, 1998) and thus allowed more precise estimates that could be more readily exploited.

If the explanation presented above holds true, then it is likely that other elements of the action-outcome loop that modulates information uncertainty should also lead to similar shifts in risk propensity. An individual with a high degree of sensorimotor competence would be likely to show risk seeking tendencies and the converse is the case for those with low sensorimotor competence. Indeed, consistent with this line of reasoning, McDougle et al (2016) demonstrated that participants with cerebellar degeneration showed risk aversion relative to neurologically intact controls on a 2 Alternative Forced Choice (2AFC) risk taking task that inspired the interceptive decision-making task employed in this thesis.

Here, we examine the impact of sensorimotor competence on risk taking through manipulating the end-effector used for action execution in our task. We suggest that participants completing the task with their non-preferred hand could present an elegant model for an agent with low sensorimotor competence (and avoid the difficulties associated with matching neurologically impaired patients with healthy control participants (Korngut et al., 2013)).

The majority of people are right handed (approximately 90%) (Caliskan & Dane, 2009; Jung & Jung, 2009; Perelle & Ehrman, 1994) and handedness is a key behavioural characteristic in motor control, with biases developing pre-birth and becoming consistent during early childhood (Fagard, 2013; Hammond, 2002; Serrien et al., 2006). Handedness has been described as: (1) one hand consistently preferred for pursue a particular task, (2) the same hand is preferred for the most of tasks to be performed, and (3) this hand is more skilled than the other in task performance (Hammond, 2002; Serrien et al., 2006). Whilst it is the case that people will also use their non-preferred hand regularly (e.g. safely manipulating a steering wheel typically requires the use of both hands) and that the non-preferred hand can be trained to do certain motor task as well as the preferred hand (Ackland & Hendrie, 2005), it is most generally the case that the non-preferred hand will typically show less accuracy and slower reaction times when compared to the preferred hand (Borod et al., 2011).

Following the argument above, using the non-preferred hand does lead to more motor noise while executing an action (Schmidt et al, 1979). For instance, when participants are asked to execute an action faster (Fitts, 1966) or execute an action with a non-preferred hand (Annett et al., 1979), participants trade-off accuracy to achieve the goal. When motor noise is high, the precision is low. Evidence suggests that the preferred hand has an advantage in learning a novel dynamic task (Duff & Sainburg, 2007; Guiard, 1987;

Hammond, 2002; Sainburg, 2002; Wang & Sainburg, 2003). Performance differences between the preferred hand and non-preferred hand have been related to a distinction in visual and proprioceptive processing (Goble & Brown, 2008; Sainburg & Kalakanis, 2017). Visual feedback might help the coordination of movement (more than without visual feedback) when the preferred hand is used in a reaching task more than when using non-preferred hand (Bagesteiro & Sainburg, 2002). Conversely, studies focusing on deafferented individuals have indicated that proprioceptive loss might be more critical for the non-preferred hand than preferred hand (Bagesteiro & Sainburg, 2003; Renault, 2018).

One study on handedness provided training first for either the preferred or non-preferred limb under normal target conditions, and then the opposite limb was tested when the target was displaced or visual feedback was rotated (Sherwood, 2014). The results indicated that participants who trained on their preferred hand (right hand) subsequently had more accurate movements when using their non-preferred hand. Additionally, the transfer from only preferred hand to non-preferred hand had a noticeable effect on final point accuracy (Pan & Van Gemmert, 2013; Sainburg & Wang, 2002) indicating that the order in which information is acquired (with a handedness asymmetry) could impact on behaviour; however, to the present knowledge, no such investigations employing decision-making tasks have been employed.

In this chapter the effect of feedback on decision making will be investigated while participants perform the motor decision-making task described in previous chapters using either their non-preferred hand or preferred hand under spatial and binary feedback conditions. We follow this up with a second experiment that employs a within subject design and asks participants to switch between hands during the experiment. For experiment 2, we expect that participants will be most risk averse in the binary feedback condition when participants complete the task with their non-preferred hand as external feedback is limited and sensorimotor noise should be relatively high, thus increasing uncertainty about the consequences of one's actions. In contrast, participants performing the task with their preferred hand in the spatial feedback condition should have the highest risk propensity. In Experiment 3, we expect to replicate these general patterns in a within subject design but also capture information transfer asymmetry, with participants performing the task with their non-preferred hand in the Binary condition after experiencing spatial feedback with the preferred hand to have a heightened risk propensity.

4.2.1 Experiment 4

4.2.1.1 Sample

Fifty-six people (aged 17-33 years; M: 20.02, SD: 3.05; 39 Female) were recruited from the University of Leeds Dentistry Department. The Edinburgh Handedness Inventory (EHI) was used to assess participant handedness (Oldfield, 1971). Two people were classified as left-handed (EHI < -40), 22 ambidextrous (-40 < EHI <40) and 33 people were right-handed (EHI > 40). All participants reported normal or corrected-to-normal vision. All participants took part in the study as a part of dentistry application. Ethical approval was obtained from the local research ethics committee (Reference 271016/MM/216).

4.2.1.2 Task

The interceptive timing decision making task has been described in previous chapters and for brevity, only the elements relevant to the experimental manipulations are described here (Figure 2.1).

Conditions were classified based on which feedback was presented to participants in the task as in Chapter 2 and 3. In the Binary condition, participants were exposed to binary feedback: whether they hit or miss the target without any other visual clue about their performance. In the Spatial condition, participants were exposed to spatial feedback where they could see their error.

4.2.1.2.1 Reward Schedule

The reward schedule has been used as it is described in Chapters 2, 3 and 4. Feedback was predetermined based on the same principles (Figure 3.6). Again, hit probability and reward functions were manipulated, and accordingly target size for each target, such that the expected value was matched in every trial and kept constant throughout the experiment. Risk was operationally defined based on the probability of hitting the target.

The target with less probability of hitting than the other is the risky target because it was less likely to be achieved compared to the other target. The participant received the associated reward value on hit trials, whereas, no points were rewarded on the miss trials. The target's location was counterbalanced. Target pairs were randomly displayed based on the same reward schedule for all participants.

4.2.1.2.2 Subjective Measures

Participants were asked to complete a post-experiment survey at the end of each condition. The survey (using a 7-point Likert scale; where 1 is totally disagree and 7 is totally agree) required participants to answer how much they agree with statements such as: "I felt on control of the outcome of the task.", "I was risk-seeking during the task'; and "The game tracked my movements accurately."

4.2.1.3 Study Design

As in previous chapters, a between subject study design was employed. Participants were randomly assigned to two different conditions: the binary feedback condition and the spatial feedback condition. Overall, participants received 100 trials. In addition to this, we include results from Chapter 3 to provide a comparison condition. Therefore, the study design can be considered as a between subject design, where feedback (spatial and binary) and used hand (preferred and non-preferred hand) are independent variables.

4.2.1.4 Statistical Analysis

4.2.1.4.1 Preliminary Analysis

The equality of variance was tested and the normality assumption for the groups was tested by using the Shapiro-Wilk Normality test. The age differences between two different conditions (Spatial and Binary Feedback) was tested using an independent t-test. Participants' responses post survey were compared between the two experimental groups using a t-test or non-parametric 2- group Mann-Whitney U Test regarding Subjective riskiness and Subjective control to investigate the subject's perception of their own riskiness and to find out if the feeling of control had been successfully perceived by participants.

4.2.1.4.2 Riskiness Analyses

To investigate riskiness behaviour throughout the experiment, an independent t test was conducted for risk propensity in the Binary feedback and spatial feedback. Mauchly's Test of Sphericity was used to indicate if the assumption of sphericity had been violated for repeated measure ANOVAs. The Levene's test was used to assess homogeneity of variance. Additionally, the results were compared to results from Chapter 3.3 (Experiment 3) by using two between subject designs. A 2 (Feedback type: Spatial vs. Binary) X 2 (Hand: Preferred hand vs. Non-preferred hand) ANOVA was conducted. The *ezANOVA* package in R was used for data analyses. Bonferroni correction was used for pairwise t test for post-hoc test.

4.2.1.4.3 Error Correction Analyses

To examine error correction, we followed the same analysis protocol described in previous chapters. The two linear models were compared by using pairwise comparison *emtrend* function in *emmeans* package. This has been used to compare the two linear models for error correction. These data will be compared with the findings from Chapter 3.3. The effect of using different hands on error correction was compared for both spatial and binary feedback type by using pairwise comparison emtrend function.

4.2.1.4.4 Switch Selection Behaviour Analyses

To investigate the switching of the level of risky behaviour, how participants change the decision from risky to safe or safe to risky regarding the outcomes and feedback, we conducted a 2 (Feedback type: Spatial vs. Binary) X 2 (Outcome: Miss vs. Hit) X 2 (Previous Choice: Risky vs. Safe) mixed design ANOVA was conducted. Mauchly's Test of Sphericity was used to indicate if the assumption of sphericity had been violated for repeated measure ANOVAs. The Levene's test was used to assess for homogeneity of variance.

4.2.2 Results

4.2.2.1 Preliminary Analysis

Participants' age in the binary feedback condition ($M=21.29$, $SD=3.93$) and participants' age in the Spatial condition ($M=19.03$, $SD=1.60$); was compared and the result shows that there is a significant difference between the two conditions ($t(28.934)=2.652$, $p = 0.012$).

The assumption of normality for spatial feedback condition subjective risk scores ($W=0.896$, $p = 0.005$) and for binary subjective risk scores ($W= 0.914$, $p = 0.04$) was violated. The binary and spatial feedback condition of subjective risk scores were not normally distributed. There was no significant difference between the variances of the two sets of data [$F(24,30)= 1.823$, $p = 0.1196$]. There was no significant differences of subjective risk ($M = 4.08$, $SD= 1.87$, $SE= 0.37$ for binary; $M = 4.87$, $SD= 1.38$, $SE= 0.25$ for spatial) between the two conditions ($t(54) = -1.819$, $p = 0.074$) (Figure 4.1B).

The assumption of normality for both spatial feedback condition subjective control scores ($W= 0.905$, $p = 0.01$) and binary subjective control scores ($W= 0.912$, $p = 0.034$) were violated. The spatial and binary feedback condition subjective control scores were not normally distributed. There was no significant difference between the variances of the two sets of data [$F(24,30)= 1.464$, $p = 0.32$]. There was no difference in subjective control ($M = 5.08$, $SD= 1.41$, $SE= 0.28$ for binary; $M = 4.81$, $SD= 1.17$, $SE= 0.21$ for spatial) between the two conditions ($t(54) = 0.794$, $p = 0.431$) (Figure 4.1A).

Since the parametric tests assume the normality of samples were violated, a non-parametric 2- group Mann-Whitney U Test was also conducted for subjective control scores between two conditions and no reliable differences emerged ($W = 448.5$, $p =$

0.298). Subjective risk scores between two conditions also showed no reliable differences (W = 297.5, p = 0.134).

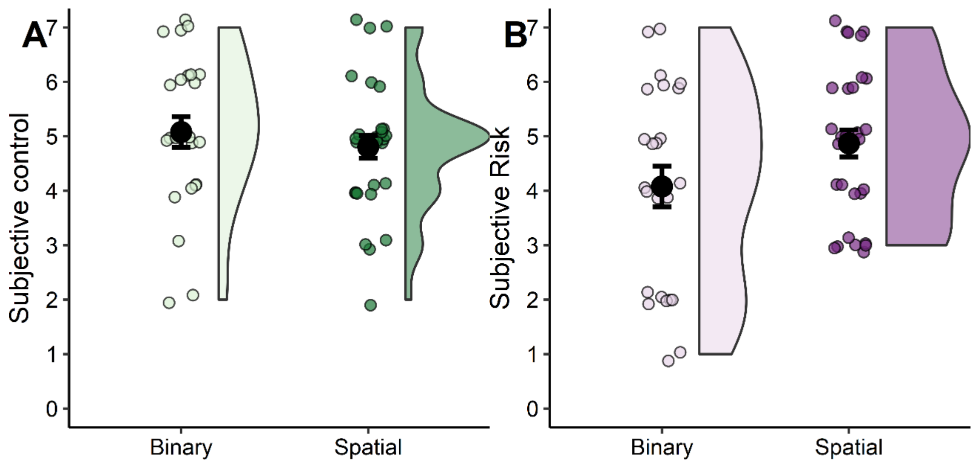

Figure 4.1 Responses from post questionnaire for each feedback type. A) Participants rated if they felt in control of the outcome of the task (higher scores indicate more control). There was no significant difference between each condition regarding subjective control as expected. B) Participant rated how risky they think they are in each session (higher indicates more risky). The subjective perception of their own selection is also aligned with the subjective control ratings. There was no significant difference between each condition regarding subjective riskiness. The black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

In summary, the subjective control results indicated that the mean of feeling in control was similar for both conditions. The subjective riskiness results indicated that both conditions showed risk seeking to a similar degree.

4.2.2.2 Primary Analyses

4.2.2.2.1 Riskiness

Whilst the pattern of decision strategies ranged only from risk-neutral to risk-seeking, there was a marked difference in target preference, with participants in the Binary condition consistently preferring to select targets with the largest width/safe options (Figure 4.2A &B) The assumption of normality for spatial feedback condition riskiness

(W=0.889, p = 0.004) for binary riskiness (W= 0.913, p = 0.036) were violated. There was significant difference between the variances of the two sets of data [F(23,29)= 2.923, p = 0.007]. The independent t-test was computed and there were significant differences in riskiness between the two conditions (t(52) = -1.517, p = 0.135). Since the parametric tests assume the normality of samples were violated, a non-parametric 2- group Mann-Whitney U Test showed that there was no reliable differences (W = 330.5, p = 0.351).

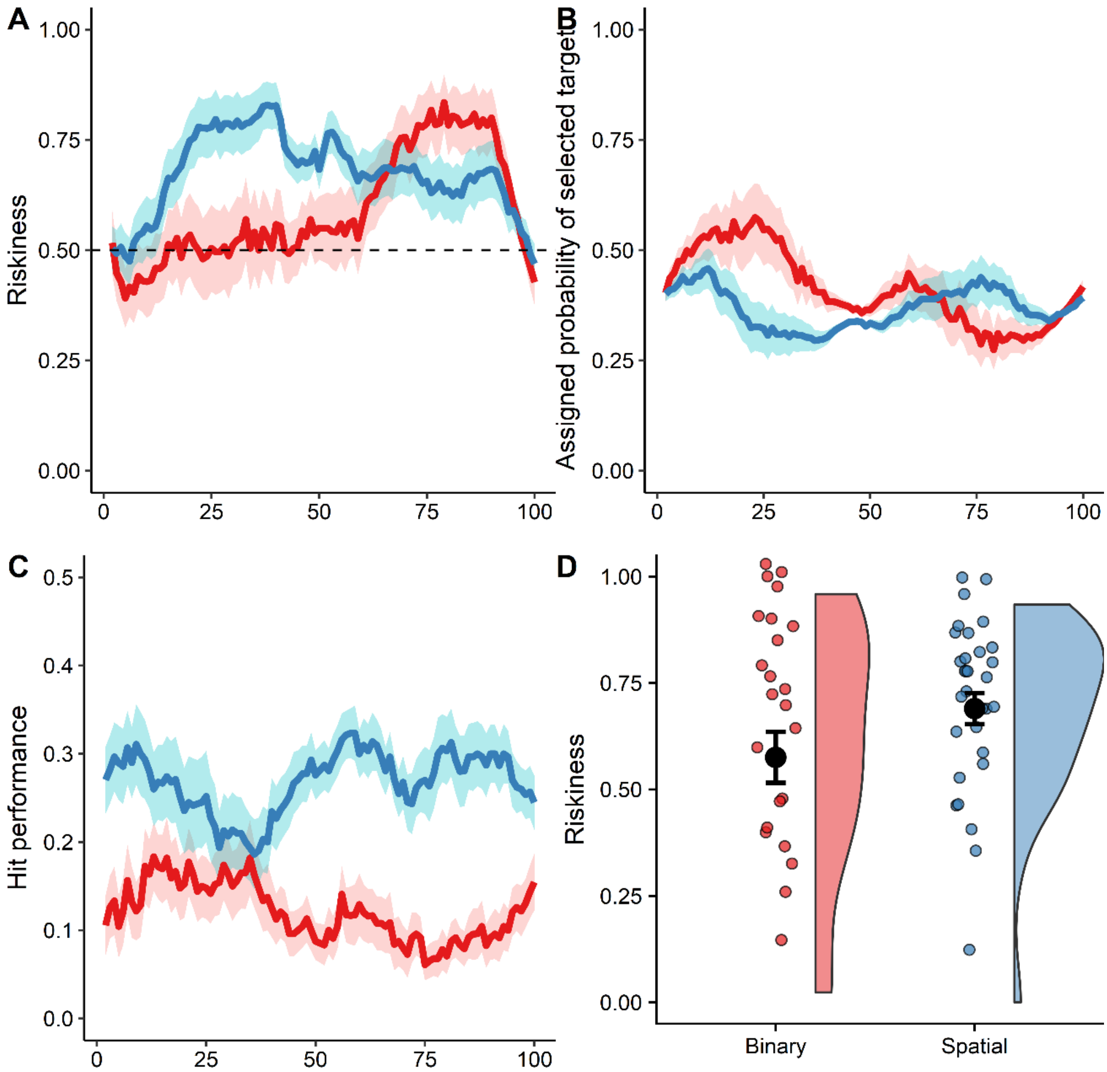

Figure 4.2 Risk propensity and hit rate according to feedback type. A)Moving average of participants' risky selections from binary values where 1 is risky and 0 is safe. Two lines represent spatial and Binary condition. Participants in the Spatial condition adopt risk-seeking behaviour compared to participants in the Binary condition throughout the experiment (from trial 1 to trial 100). Participants in the Binary feedback became risk-seeking after the first 50 trials. B) Participants selection of the probability of target represented as moving average graph. The participants in the Spatial condition are selected targets with risky probabilities more than participants in the Binary condition which supports the evidence from A&D. C) The graph represent the actual hit performance between two conditions, which is quite low for both conditions. However, the hit performance of participants in the Spatial condition mostly higher than participants in the Binary feedback. Even though participants in both feedback conditions made a riskier choices after 50 trials, still hit performance is relatively low in the Binary feedback. As mentioned, hit performance is cofounded by selected target size between two conditions. D) The graph represents the mean of riskiness between Binary and Spatial conditions. It is clear that participants in the Spatial condition were more risk-seeking than participants in the Binary condition. The data points show the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

To investigate whether participants changed the degree of risky behaviour they exhibited from beginning of the experiment to the end, a 2 (Feedback type; binary, spatial) by 2 (Sequence; First, Second) mixed design ANOVA was conducted. There was no main effect of sequence or feedback. Interestingly however, there was a significant interaction [$F(1,54)= 5.062$, $p = .028$, $\eta_G^2 = 0.03$]. Participants in the binary feedback were more likely to be safer in the first 50 trials (M = 0.48, SD = 0.36, SE = 0.07) compared to the last 50 trials (M = 0.68, SD = 0.28, SE = 0.06; Figure 4.3).

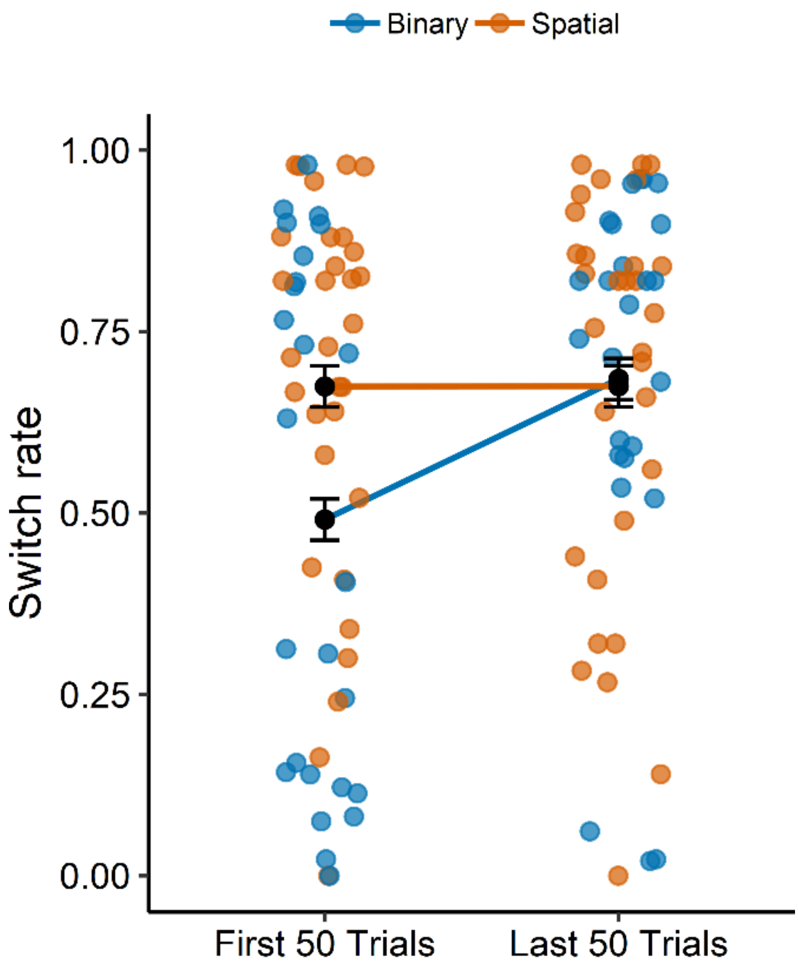

Figure 4.3 Risk Propensity in Early and Late Stages as a Function of Feedback. This graph represents the riskiness data for the first 50 trials and the last 50 trials in both spatial (orange) and binary (blue) feedback. Participants in the spatial feedback condition were greater risk-seekers, but participants in the binary feedback condition gradually became risk seeking in the last 50 trials compared to the first 50 trials. Error bars represent +/-1 standard error of the mean.

The comparison with the findings from the previous chapter showed no reliable difference between hand used as well as no reliable interaction; however, there was a significant differences between feedback type [F(1,115) = 7.11, p = 0.008, η_G^2 = 0.058); however, the Levene test of homogeneity was violated [F(3,115) = 2.949, p = 0.036]. When homogeneity of variance is violated, there is a greater probability of overestimating the significance value.

4.2.2.2.2 Error Correction

To investigate participants motor performance, we examined the degree to which participants corrected their motor errors on a trial by trial basis. The linear models from two conditions are represented in the Table 5.

Table 5 The results of fitted linear model for each condition.

Feedback type	ß	df	Lower confidence level interval	Upper confidence level interval
Binary	-0.163	5286	-0.186	-0.140
Spatial	-0.774	5286	-0.822	-0.727

The linear model for binary feedback showed a small value for slope suggesting that the model is skewed from the idealised error correction model. On the other hand, the linear model for spatial feedback was very close to the ideal error correction model. The pairwise comparison between the two models showed that these two models were significantly different from each other (t(5286)= 22.820, p<.0001; (Figure 4.4).

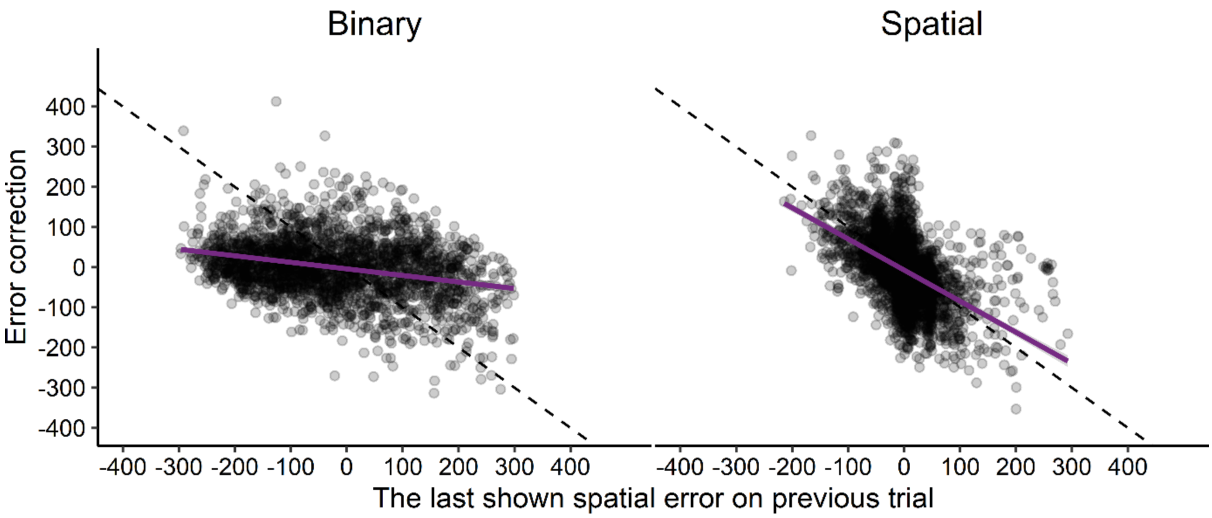

Figure 4.4 Error correction based on previous feedback. The x axis represents the value of the last shown spatial error value (mm) on previous trial, and the y axis represents the difference between last seen spatial error value and the current spatial error value (mm) on a given trial. An ideal observer who corrects error would fall along the dashed line. The purple line is the linear fit to the actual data. In the spatial feedback condition, the linear model approaches the ideal line, however, the linear model in the Binary feedback condition does not. The correction in the binary feedback condition should be intrinsic error correction based on the lack of external error information in knowledge of result, whereas, participants in the Spatial condition actually see the spatial feedback in every trial.

Error correction comparison with the findings from Chapter 3.3

To investigate how error correction might be affected by performing the task using the non-preferred hand, the data was compared with the findings from Chapter 3.3 (see Figure 4.5). The binary feedback and spatial feedback condition were separated (see Table 6). In the spatial feedback condition, the models of preferred hand and non-preferred hand models showed that they were significantly different to one another ($t(5850)= 2.07$, $p=0.038$). In the binary feedback condition, the models of preferred hand and non-preferred hand models showed that these two models were not significantly different to each other ($t(5279)= -0.547$, $p=0.584$).

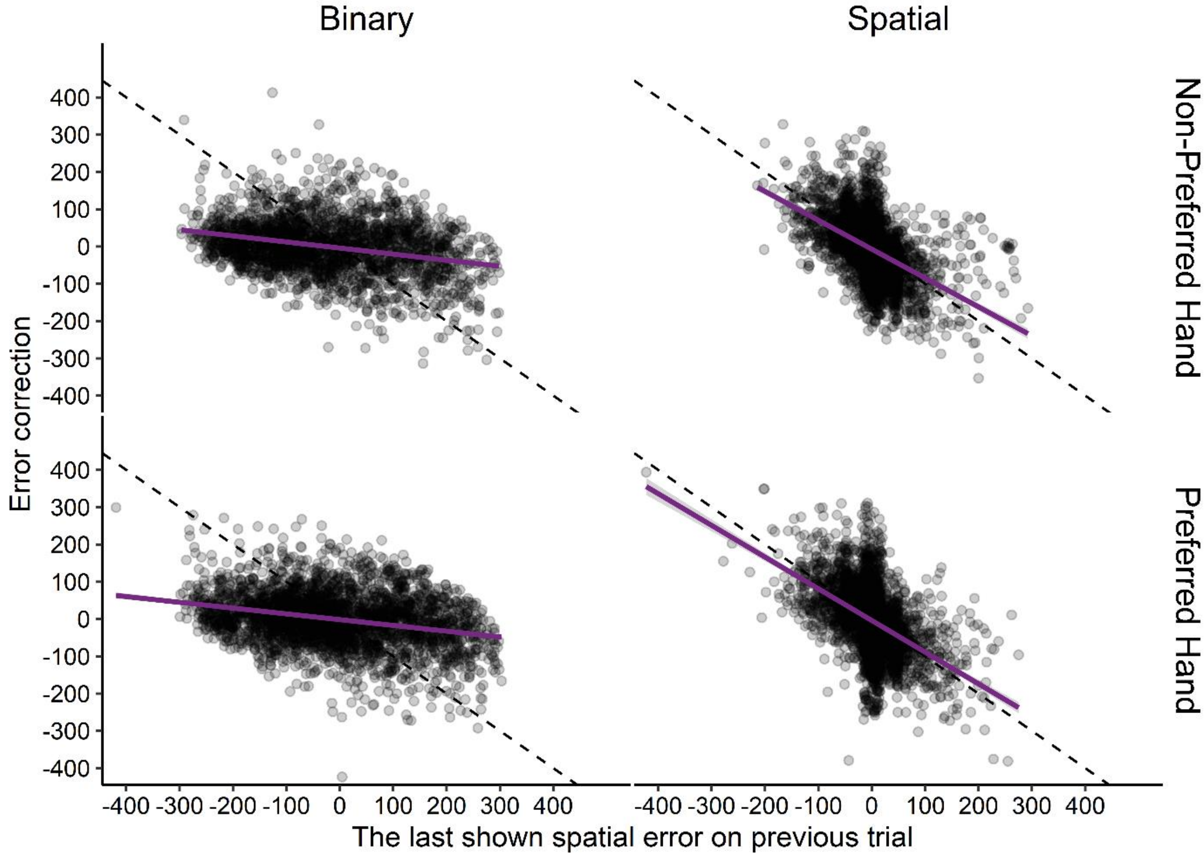

Figure 4.5 Error correction based on previous feedback. On the x axis, the value of last seen spatial error value (mm) on previous trial. On the y axis, the differences between their last seen spatial error value and their current spatial error value (mm) on a given trial between used hands and feedback types. The purple line in the Spatial feedback condition shows that the linear model of participants' correction approaches the ideal error correction. However, the linear model in the Binary feedback condition does not present a well-adjusted error correction. The correction in the binary feedback condition should be intrinsic error correction based on the lack of external error information in knowledge of result, whereas, participants in the Spatial condition actually see the spatial feedback in every trial.

Consistent with the previous experiments in this thesis, the result show that participants in the spatial feedback condition were able to more effectively make use of spatial error information to correct their performance in the following trial. In the Spatial condition, participants using preferred hand seems to differ from those using non-preferred hand, where using preferred hand seems to have an advantage on correcting spatial error according to last shown spatial error.

Table 6 The results of fitted linear model between the current study (Non-preferred Hand) and the chapter 3.3 (Preferred Hand).

Feedback type		ß	df	Lower confidence level interval	Upper confidence level interval
Binary	NPH (4.1)	-0.163	5279	-0.185	-0.141
	PH (3. 2)	-0.155	5279	-0.174	-0.135
Spatial	NPH (4.1)	-0.774	5850	-0.825	-0.724
	PH (3. 2)	-0.850	5850	-0.901	-0.800

4.2.2.2.3 Switch Selection Behaviour

Lastly, we investigated whether people switched decision from a risky option to a safe option and vice versa- when they had a miss or a hit. A 2 (feedback type; binary, spatial) by 2 (outcome; miss, hit) by 2 (previous selection; risky, safe) mixed design ANOVA was conducted. There were main effects of previous selection [$F(1,53)= 13.211$, $p < .0001$, $\eta^2_G = 0.12$] and outcome [$F(1,53)= 24.789$, $p < .0001$, $\eta^2_G = 0.035$]. Participants were more likely to switch if the previous selection was safe (M = 0.36, SD = 0.24, SE = 0.02) compared to risky (M = 0.20, SD = 0.21, SE = 0.02) (Figure 4.6B). Participants were more likely to switch after a miss (M:0.32, SD=0.24, SE: 0.02) than a hit (M:0.24, SD=0.23, SE: 0.02) (Figure 4.6). There was also a three way interaction between feedback type, outcome and previous selection [$F(1,53)= 11.868$, $p = .0001$, $\eta^2_G = 0.02$] (Figure 4.7).

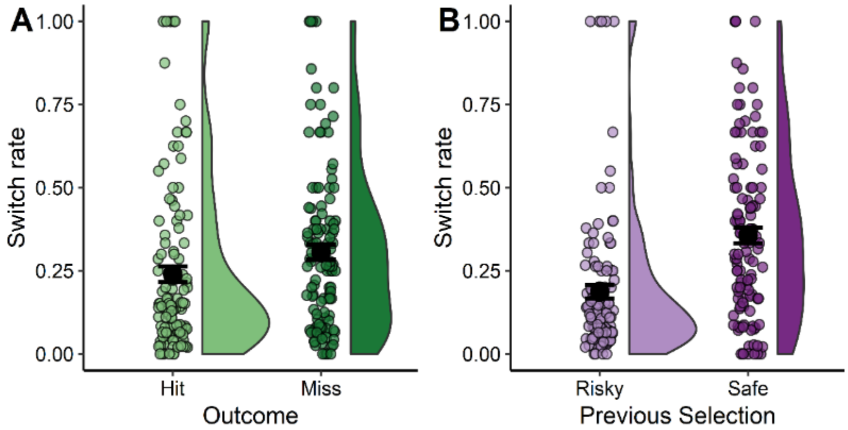

Figure 4.6 Switch rate of participants based on the previous selection. The graphs show the switch rate of participants based on their previous selection. A) Participants were more likely to switch after a miss outcome, which is what we would expect. B) Participants were also more likely to switch the selection after a safe selection, whereas, they were more likely to stick the selection after a risky decisions. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

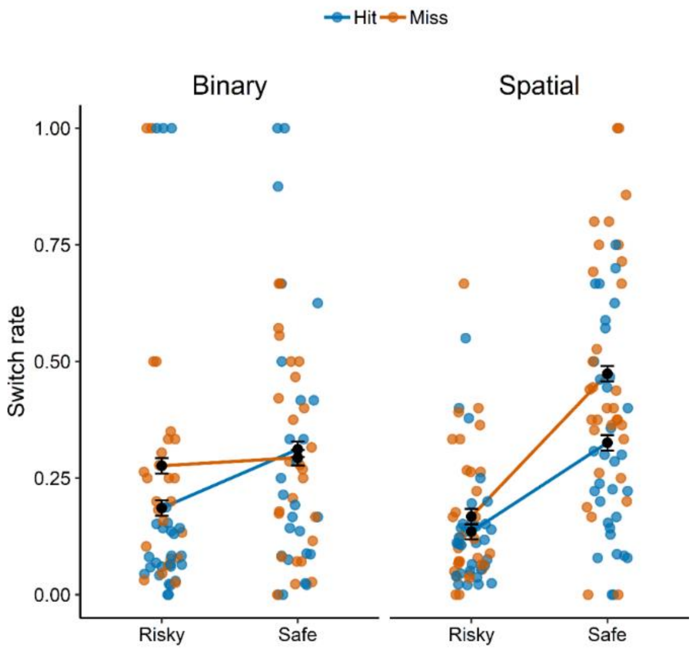

Figure 4.7 Switch rates as a function of feedback, choice selection and success. Participants in the Binary condition had a similar switch rate for a miss after both risky and safe selection; however, they switched more after safe selection then risky selection when the outcome was hit. In other words, the switch rate for miss outcome was similar after both safe and risky in the Binary feedback condition, whereas, the switch rate for hit outcome was higher after safe selection than after risky selection in the Binary feedback. Participants in the Spatial feedback condition had highest switch rate after safe selection when the outcome is miss, this was higher than after risky selection for miss outcome, too. Switch rate in the Spatial feedback increased after safe selection in hit outcomes compared with after risky selection after hit. However, switch rate for miss outcome was lower than switch rate in miss outcomes. Although, participants are more likely to have similar level switch rate after both miss and hit outcome when the previous selection is risky. This trend disappeared for selection after safe choice. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

In summary, participants in the spatial feedback condition adopted a well-adjusted error correction, significantly different than for the binary feedback condition. Spatial feedback resulted in less switching after a risky decision than a safe decision. Binary feedback led to risk seeking behaviour in the last fifty trial. Switching rates after a risky or safe selection were modulated by feedback type, previous selection and outcome. After a miss trial, participants were more likely to switch safe decision in the Spatial feedback compared to switch from risk to safe. For hit trials the trend was similar but did not differ based on feedback type. Lastly, participants did not change the amount of switch from safe to risk after a safe choice in the Binary condition.

4.2.3 Discussion

Experiment 4 sought to investigate the relationship between feedback and motor competency. In contrast to our predictions, there was no increase in risk as information and competency increased. Instead, we found that participants who needed to rely on intrinsic feedback (those who received binary feedback, did not receive any performance error information) eventually adopted risk seeking behaviour when they performed the whole task with their non-preferred hand. The potential functional meaning of these results will now be discussed in more detail.

On first examination, the mean of riskiness was not found to differ significantly dependent on the type of feedback given; however, when this relationship was examined in more detail, the relationship between riskiness and feedback varied across the experiment. Where binary feedback was provided, a gradual increase in risk seeking behaviour was observed. If binary feedback provides a closer approximation of proprioceptive feedback (Adams, 1971), then this finding is as would be expected, as current literature states that the non-preferred hand relies more on proprioceptive feedback in general (Goble, Lewis, & Brown, 2006; Renault, 2018; Sainburg & Kalakanis, 2017). Therefore, for participants using their non-preferred hand, it could be why binary feedback resulted in an increase in risk seeking behaviour.

From detailed analysis, a further and unexpected result was obtained; although, the participants who received binary feedback demonstrated a gradual risk seeking strategy (last 50 trials), participants in the Spatial condition appeared to perform better in error correction in the Spatial condition. Participants’ perception of their own performance might be higher than what they expected to perform at the beginning of the trial. This might lead over-confidence and they might result in biasing towards risk seeking (Cohen, 1993).

A limitation of this study was that it could not evaluate whether there was an effect of using both the preferred and non-preferred hand within an individual. As such, a further study was performed where both the preferred hand and non-preferred hand were used, to allow for the comparison of the differences this produced when in the presence of either binary or spatial feedback.

4.3 Experiment 5

The previous study indicated an interplay between feedback and motor competence on risk taking. In this study, we delve deeper into this relationship through employing a within subject design in which participants are asked to switch hands half way through the experiment.

The literature on interlimb transfer suggests an asymmetry in information carryover – with participants learning more about a task when it is performed first with the preferred hand when subsequently performed by the non-preferred hand than the opposite order (Pan & Van Gemmert, 2013; Robert L. Sainburg & Wang, 2002). We expected that this information transfer asymmetry would also have consequences for decision-making.

4.3.1 Methodology

4.3.1.1 Sample

Eighty-eight people (aged 17-33 years; M: 20.01, SD: 3.30; 61 Female) were recruited from the University of Leeds Dentistry Department. The Edinburgh Handedness Inventory (EHI) was used to assess participants handedness (Oldfield, 1971). Three people were classified as left handed (EHI < -40), 24 ambidextrous (-40< EHI<40) and 61 people were right handed (EHI > 40). All participants reported normal or corrected-to-normal vision. The approval was obtained from the local research ethics committee (Reference 271016/MM/216).

4.3.1.2 Task

The same task in Chapter 4.2.1 (Experiment 4) was used. For more details please see (4.2.2.2).

4.3.1.3 Study Design

Participants were randomly assigned to two different conditions: binary feedback condition and spatial feedback condition. Each participant in each condition used first their preferred hand in the first block, then used their non-preferred hand in the second block, or vice versa. The order in which participants completed the task was counterbalanced across subjects.

4.3.1.4 Statistical Analyses

4.3.1.4.1 Primary Analyses

The post-survey questions were taken once after each experimental session. The same analyses described as in Chapter 4.2.1 (Experiment 4) was used here.

4.3.1.4.2 Risk propensity Analyses

To investigate riskiness behaviour throughout the experiment, a 2 (feedback: Spatial vs. Binary) X 2 (Used hand: Preferred hand vs Non-preferred hand) X 2 (Order; Preferred hand first, Non-preferred hand first) mixed design ANOVA was conducted. Bonferroni correction was used for pairwise t test post-hoc. The generalized Eta-Squared measure of effect size is reported. Mauchly's Test of Sphericity was used to indicate if the assumption of sphericity had been violated for repeated measure ANOVAs. Levene's test was used to assess for homogeneity of variance.

4.3.1.4.3 Error Correction Analyses

The same approach as in Experiment 4was adopted.

4.3.1.4.4 Switch Selection Behaviour Analyses.

The same approach as in Experiment 4 was adopted.

4.3.2 Results

4.3.2.1 Preliminary

Participants' age in the binary feedback condition (M=19.71, SD=2.57) and participants' age in the Spatial condition (M=20.32, SD=3.90); was compared and the result showed that there was no significant difference between two conditions ($t(74.44)=-0.867$, $p = 0.389$).

Subjective risk and subjective control scores were compared by using an independent t test. The assumption of normality for spatial feedback condition subjective risk scores ($W=0.932$, $p = 0.013$) and for binary subjective risk scores ($W= 0.935$, $p = 0.018$) were violated. The binary and spatial feedback condition subjective risk scores were not normally distributed. There was no significant difference between the variances of the two sets of data [$F(42,43)= 0.976$, $p = 0.939$]. There was no significant differences in subjective risk (M = 4.07, SD= 1.83, SE= 0.28 for binary; M = 3.91, SD= 1.85, SE= 0.28 for spatial) between two conditions ($t(85) = 0.407$, $p = 0.685$).

The assumption of normality for both spatial feedback condition subjective control scores ($W= 0.931$, $p = 0.011$) and binary subjective control scores ($W= 0.94$, $p = 0.027$) were violated. The spatial and binary feedback conditions subjective control scores were not normally distributed. There was no significant difference between the variances of the two sets of data [$F(42,43)= 1.095$, $p = 0.767$]. The independent t test results showed that there was no reliable differences in subjective control (M = 3.79, SD= 1.78, SE= 0.27 for binary; M = 3.89, SD= 1.70, SE= 0.26 for spatial) between the two conditions ($t(85) = -0.256$, $p = 0.798$).

Since parametric tests assume normality assumptions have been violated, a non-parametric 2- group Mann-Whitney U Test was also conducted for subjective control scores between the two conditions. The results showed no reliable difference (W = 917. p = 0.806). Subjective risk scores between two conditions also showed no reliable differences (W = 990.5. p = 0.705).

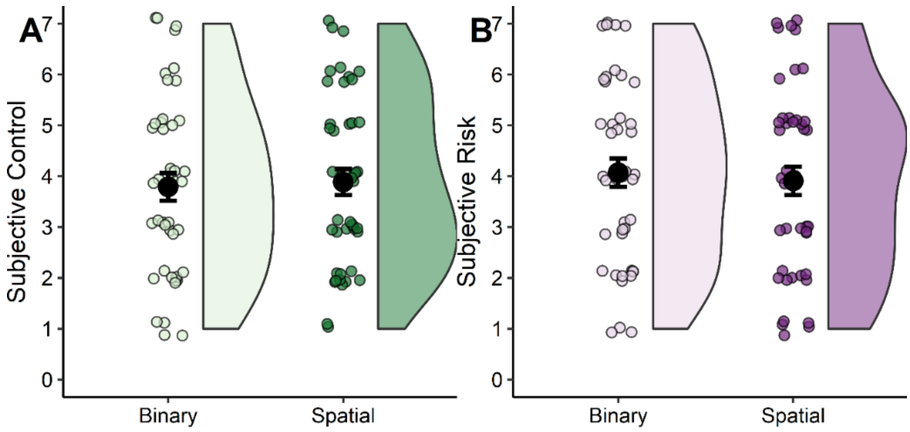

Figure 4.8 Responses from post questionnaire for each feedback type. A) Participants rated if they felt in control of the outcome of the task. There was no significant difference between each condition regarding subjective control as expected. B) Participant rated how risky they think they are in each session. The subjective perception of their own selection is also aligned with the subjective control ratings. There was no significant difference between each condition regarding subjective riskiness. The data point shows the individual responds and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

To sum up, participants' age was not significantly different between conditions. The subjective control results indicated that participants in both conditions felt control to similar degrees (Figure 4.8A). The subjective riskiness results indicated that both conditions were risk seekers to a similar degree (Figure 4.8B).

4.3.2.2 Primary Analyses

4.3.2.2.1 Riskiness

A 2(Feedback type: Spatial vs. Binary) X 2(Used hand: Preferred hand vs. Non-preferred hand) X 2 (Hand switch: Preferred hand first vs. Non-preferred hand first) ANOVA was conducted. There was a main effect of feedback [$F(1,83)= 4.145$, $p = 0.045$, $\eta_G^2 = 0.037$],

(Figure 4.9A&B). In addition, there was a marginal interaction between used hand and feedback [F(1,83)= 3.516, p = 0.064, η_G^2 = 0.009] (Figure 4.10); however, there was no other significant result. The Binary condition (M = 0.63, SD = 0.26, SE = 0.04) showed higher risk seeking behaviour than the Spatial condition (M = 0.52, SD = 0.28, SE = 0.04) (Figure 4.9C).

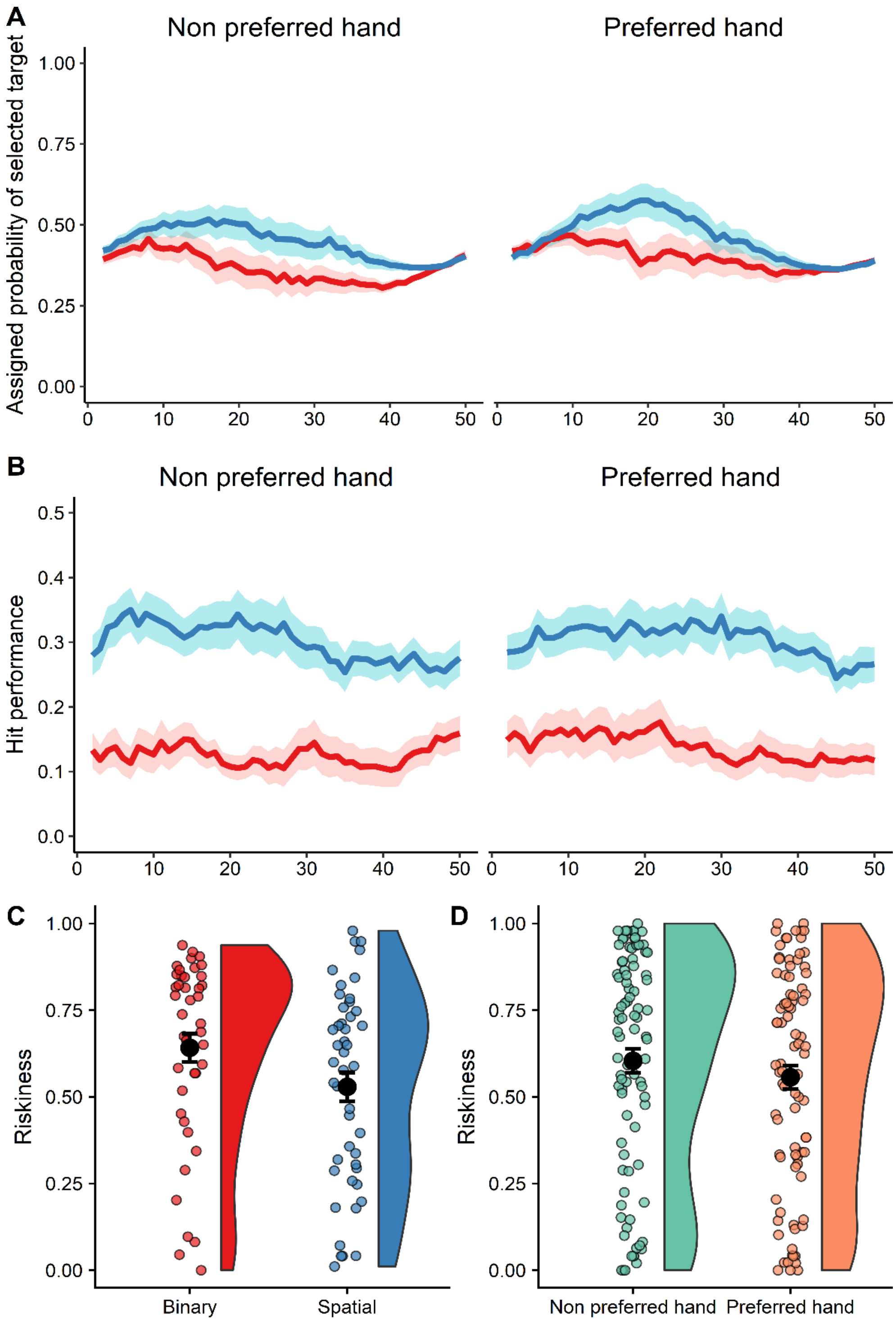

Figure 4.9 Risk propensity and hit performance according to feedback type and hand. Binary (Red) or Spatial (blue) feedback group for individuals using their Preferred (orange) or Non-Preferred (green) hands. A) Participants in the Binary feedback condition selected targets with smaller probabilities (smaller target size) than participants in the Spatial feedback condition. B) Participants actual hit performance. Participants in the Binary feedback are lower actual feedback. C) Participants in the Binary condition are more likely to be risk seekers. D) Participants may appear to be more risk seeking when using their non-preferred hand; however, there were no statistically reliable differences between hands observed. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

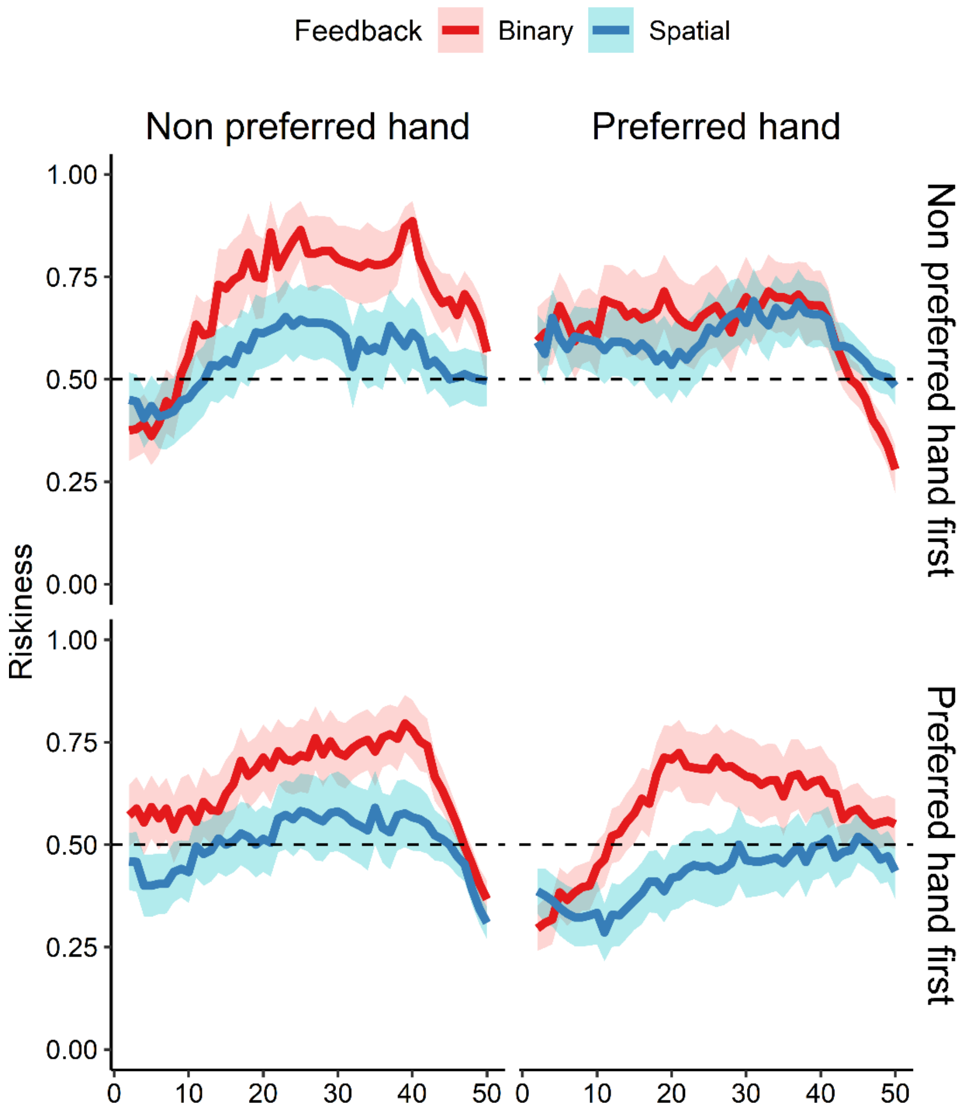

Figure 4.10 The interaction between Order and Feedback. The red and blue lines represents binary and spatial feedback respectively. The participants who used their non-preferred hand first are more risk seeker in the Binary feedback condition than the participants in the Spatial feedback condition. However, after switching hand the participants in the Spatial feedback condition became as much risk seekers as participants in the Binary feedback condition. Nevertheless, this interaction is only marginally significantly different. Light coloured ribbons represents the standard error.

Lastly, same analysis was run on data from the participants whose handedness were measured 100 Edinburgh Handeness Inventory (EHI) (see Appendix 1).

4.3.2.2.2 Error Correction

To investigate motor performance, we looked at the degree of error correction participants displayed following each trial per condition. The linear models from two conditions are represented in Table 7. The linear model for binary feedback showed a small value for slope suggesting that the model is skewed from the idealised error correction model. On the other hand, the linear model for spatial feedback was very close to the ideal error correction model. The pairwise comparison between the two models showed that these two models were significantly different from each other ($t(8271)= 36.485$, $p<.0001$) (Figure 4.11).

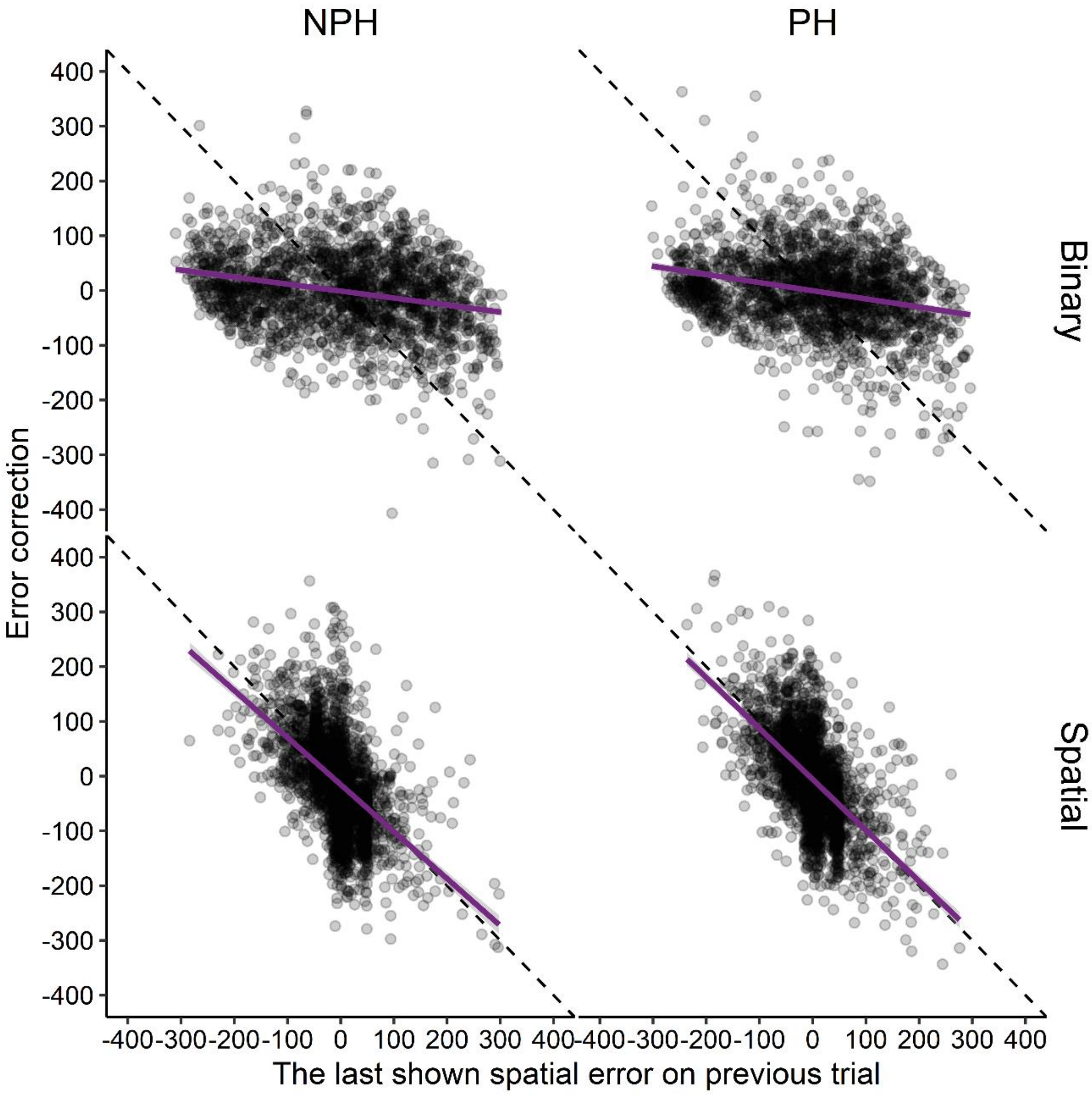

Figure 4.11 Error Correction Rates per Condition. On the x axis, the value of last seen spatial error (mm). On the y axis, the differences between their last seen spatial error value and their current spatial error value (mm). An ideal observer who would correct the error accordingly has been shown as dotted line in the graphs. In the graph participants purple line in the Spatial feedback condition shows that the linear model of participants' correction approaches the ideal error correction. However, the linear model in the Binary feedback condition does not present a well-adjusted error correction. The correction in the binary feedback condition should be intrinsic error correction based on the knowledge of result, whereas, participants in the Spatial condition actually see the spatial feedback in every trial.

To investigate the differences between non-preferred hand and preferred hand, the binary and spatial feedback conditions were examined separately. In the spatial feedback condition, the models of preferred hand and non-preferred hand showed that they were not significantly different from each other (t(4400)= 1.794, p=0.073). In the binary feedback condition, the models of preferred hand and non-preferred hand models showed that these two models were not significantly different from each other ($t(3867) = 1.307$, $p=0.191$).

Table 7 The results of fitted linear model for each condition. NPH = Non-preferred hand sessions and PH = preferred hand sessions.

Feedback type		ß	df	Lower confidence level interval	Upper confidence level interval
Binary	NPH	-0.128	3867	-0.149	-0.106
	PH	-0.149	3867	-0.173	-0.125
Spatial	NPH	-0.859	4400	-0.913	-0.805
	PH	-0.929	4400	-0.983	-0.875

4.3.2.2.3 Switch Selection Behaviour

To investigate switching behaviour, a 2 (Feedback type: Spatial vs. Binary) X 2 (Outcome: Miss vs. Hit) X 2 (Previous Choice: Risky vs. Safe) ANOVA was conducted. There was a significant difference of feedback and outcome interaction [$F(1,84)= 5.030$, $p = 0.027$, $\eta^2_G = 0.003$] (Figure 4.12C&D), as well as feedback and previous selection interaction [$F(1,84)= 4.644$, $p = 0.034$, $\eta^2_G = 0.03$] (Figure 4.12A&B). (see Table 8 for mean values)

Table 8 Values of mean, standard deviation and standard error.

	Mean	sd	se
Previous selection (Safe)	0.31	0.24	0.02
Previous Selection (Risky)	0.27	0.27	0.02
Hit	0.28	0.26	0.02
Miss	0.30	0.25	0.02

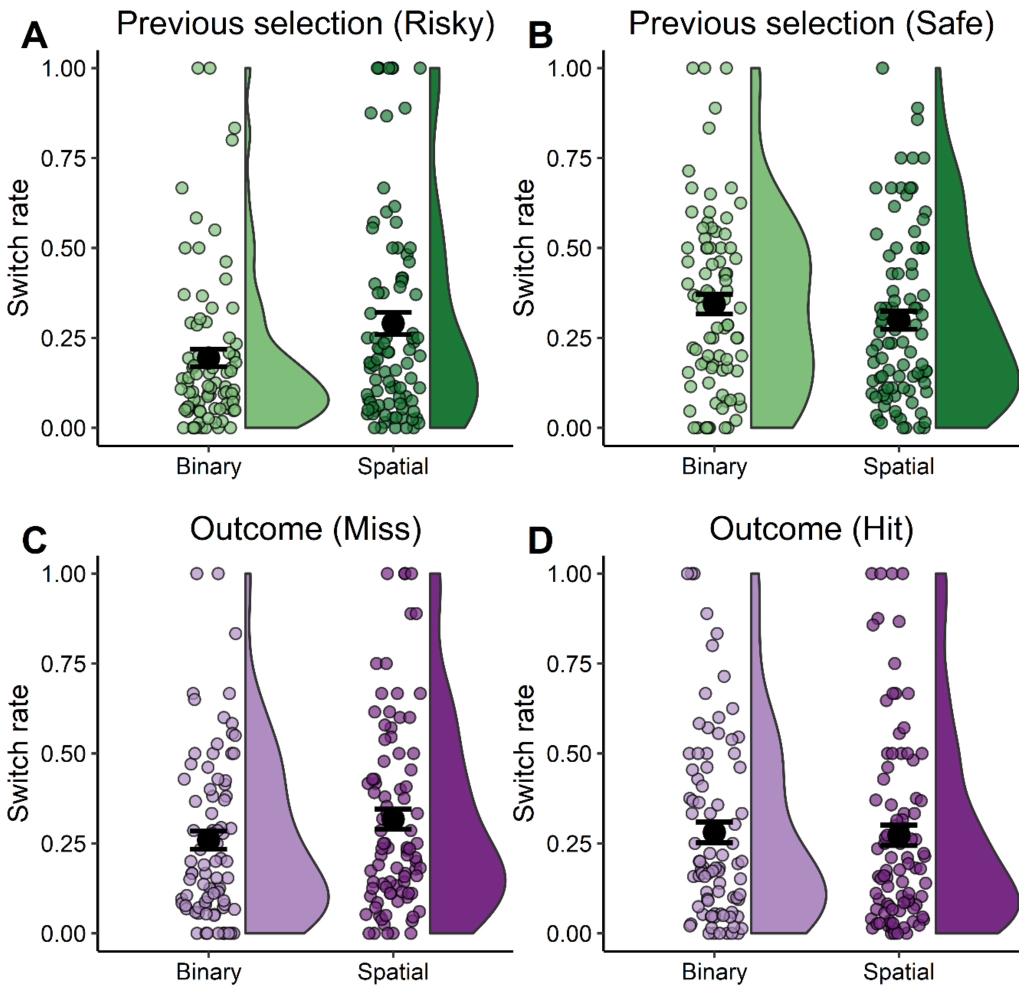

Figure 4.12 Switch rate of participants based on the previous selection. When the previous selection is risky, participants in the Spatial feedback condition were more likely to switch compared to the participants in the Binary feedback condition. However, when the previous selection is safe, the participants in the Binary feedback condition are more likely to switch compared to Spatial condition. Participants in the Binary feedback condition switch more after a safe previous selection than risky selection. These graphs might confirm that participants in the Binary feedback condition were more likely to be risk seekers than participants in the Spatial condition (A&B). (C) Participants in the Spatial feedback condition were more likely to switch after a miss than participants in the Binary feedback condition. (D) Participants in the Binary and spatial feedback condition have a similar switch rate after a hit. The data point shows the individual means and the black circle represents the group mean. The error bars represent +/- 1 standard error of the mean.

4.3.3 In summary, participants in the Binary condition showed significantly more risky behaviour than participants in the Spatial condition. Using the non-preferred hand had a marginal effect on risk propensity of the participant in the spatial feedback condition when using the preferred hand later on. Binary feedback led to less accurate data correction than spatial feedback. Discussion

The main findings from Experiment 4 suggested that providing only binary feedback (hit or miss) to participants using their non-preferred hand led them to increase their risk seeking behaviour, when compared to those who were provided with more detailed knowledge of their performance. To confirm whether there is a transfer effect of motor competence from one hand to another on choice behaviour we performed a second experiment employing a within subjects design. The results showed that providing binary feedback led to an increase in risk seeking behaviour, and this was the case irrespective of whether the preferred or non-preferred hand was used.

This finding, that only receiving knowledge of the result leads to an increase in risk seeking when compared to those who receive knowledge of their performance, may appear contradictory to both the result of the previous chapter and current literature (McDougle et al., 2016). In general, whilst using the preferred hand visual external feedback is most advantageous, and whilst using the non-preferred hand proprioceptive feedback might be more advantageous (Renault, 2018; Sainburg & Kalakanis, 2017); however, some previous motor control studies have shown that both the preferred and the non-preferred hand can benefit from receiving different kinds of feedback (Duff & Sainburg, 2007; Renault, 2018; Sainburg & Kalakanis, 2017). Since being provided only with knowledge of the result does not confer any visual external feedback on their performance, participants who received binary feedback might have to rely only on proprioceptive feedback. Relying on proprioceptive feedback might have resulted in the increase in risk seeking behaviour observed whilst using their non-preferred hand for those in the Binary condition.

The sample studied in the current study was unusual compared to the general population: heavily ambidextrous (28%) compared to 1 % (Rodriguez et al., 2010) or 5% (Rigal, 1992) of the general population that is classified as ambidextrous. However, some research on handedness suggest that ambidexterity in populations is greater than has been reported; instead there might be a shift to be right handed because of social pressure (Annett, 1998). Handedness has been described as on a spectrum with strong left and strong right hand on either ends (Annett, 1970). For example, people who are left handed, might prefer to write with their right hand. In fact ambidexterity in population is suggested to be 30% of the population (Annett, 1967). To be able to measure handedness in the current study, Edinburgh Handedness Inventory was used (EHI) which measures handedness on a spectrum (Annett, 1998; Oldfield, 1971). In the current study the handedness degree on EHI varied from -70 to 100. It may be that those who are able to use both their hands respond differently when using their preferred and non-preferred hand. As such, this may have had an effect on their risk propensity, and the high number of ambidextrous participants in this study may have somewhat contaminated the results observed.

The effect of feedback whilst performing a motor task, whilst using the preferred and non-preferred hand, on the participants risk propensity is still an understudied area of research. Indeed, the lack of a complete explanation for the findings of this study indicated that further investigation was required. In Chapter 5, this was provided through the design of a new study, where the feedback the participants received switched from knowledge of performance to knowledge of result (or vice versa) whilst they used both their preferred and non-preferred hand for the motor control task.

Chapter 5 : The Combined Impact of Outcome Information and Competency on Sensorimotor Risk Taking

5.1 Abstract

The previous chapters have demonstrated that the format in which feedback is presented (binary vs spatial end point information) can have a substantial impact on an individual's risk propensity in a decision-making task with large sensorimotor demands: The more information (i.e. spatial) one is provided about their motor execution, the less risk aversion they exhibit. The previous experiments have also shown motor competency (with preferred and non-preferred hand used as analogues of competency) in action execution modulates choice selection. In this experiment, the combined effect of these phenomena is examined by asking whether information modality and motor competency can have an additive impact on risk propensity. To this end, participants performed a decision-making task involving judgements about the ability to intercept selected targets for reward. A mixed groups design was employed with participants using their preferred or non-preferred hand (independent groups) performing an interceptive timing task with both spatial and binary feedback (order counterbalanced between participants). The results demonstrate that, for both groups (irrespective of hand) the participants who received binary feedback first, became more risk seeking when they receive spatial feedback; however, participants who received spatial feedback first kept more or less the same degree of risk seeking behaviour even whenthey received binary feedback in the second half. Also consistently, spatial feedback resulted in better error correction than binary feedback. These results are consistent with the idea that the accumulation of information about one's own motor performance is a key determinant for subsequent risky choice behaviour.

5.2 Introduction

Results from the previously reported experiments in this thesis have indicated that the amount of risk propensity exhibited by an individual in sensorimotor decision making may vary according to: (i) the degree of information available to the agent about their performances (operationalised through manipulating end-point feedback; spatial vs binary outcomes); and (ii) the sensorimotor competency to effectively carry out the action (operationalised by asking participants to complete the task with their preferred or non-preferred hand).

These results indicate that the factors modulating action evaluation and action execution both impact on choice selection. However, the results also raise a number of outstanding questions about how these parameters interact over time to feed into choice selection. For example, once information about their actions is provided to an agent through spatial feedback, does the impact of this diminish through subsequent presentations of binary feedback? In other words, do we see a decay effect of information on choice selection?

Evidence from research on sensorimotor control indicates that people seem to adopt strategies to maximize the expected gain, by combining prior information and the noisy sensory input (Körding & Wolpert, 2004; Trommershäuser et al., 2008; Vaziri, Diedrichsen, & Shadmehr, 2006). As conceptualised by Bayesian decision making theory, the amount and degree of prior information one brings to the table in a decision making task is important in determining the posterior (Edwards et al., 1963; van de Schoot, Winter, Ryan, Zondervan-Zwijnenburg, & Depaoli, 2017). Indeed, empirical demonstrations have shown that even with the same observations, different priors can lead to different posterior (Edwards et al., 1963; Vilares, Howard, Fernandes, Gottfried, & Kording, 2012) and thus bias choice selection.

Therefore, receiving different feedback (spatial and binary), even with the same task outcome, might generate qualitatively different internal models and accumulate different quantities of evidence due to the precision of information available for each feedback presentation mode. Information quantity could account for the results seen in the previous chapters- participants who have available, and can accumulate, more information are able to exploit (choose riskier options) in comparison to scenarios where information quality is degraded. In this way, we would expect that participants who receive binary feedback and then spatial feedback will be able to exploit more in the second condition (thus replicating a previously observed pattern of results). But we also expect participants exposed to spatial feedback first to maintain their level of risk appetite in the Binary condition as they should have built up a sufficiently accurate model of the task to be able to continue to exploit in this impoverished feedback condition.

In the previous chapter, the findings suggested that people performing a task with their non-preferred hand seemed to adopt different risk-taking strategies when compared with those performing with their preferred hand. The proposed explanation posits that using the non-preferred hand might manipulate the motor competence of the participants, which might change their risk propensity when performing a motor task (McDougle et al., 2016). More motor competence might cause riskier decisions. The reason why this occurs might be that the motor noise derived from the action would be higher while performing with the non-preferred hand compared with preferred hand (Annett et al., 1979), which is related to the controlling signal for an action (Todorov, 2005). Therefore, motor competence might be an important variable to investigate. The assumption, that using the non-preferred hand would generate more motor noise leaves us to expect that these participants would be more risk averse.

In terms of feedback type, literature suggests that while performing tasks with the non-preferred hand, people seem to take advantage of different information from feedback. For example, proprioceptive feedback seems to be more advantageous for using the non-preferred hand; whereas, visual feedback seems to be more advantageous for using the preferred hand (Bagesteiro & Sainburg, 2003; Sainburg, 2002; Sainburg & Kalakanis, 2017) on a sample of deafferented individuals (Renault, 2018). In the present task, participants receiving spatial feedback should have both proprioceptive as well as visual feedback; whereas, participants in the Binary condition would not have the visual feedback. Thus, we predict that that receiving more information would generate more risk-seeking behaviour, whilst performing a motor task with the non-preferred hand. This would be where participants performing with spatial feedback first might have a higher level of risk propensity when compared with those receiving binary first; and that after spatial feedback the equivalent level of risk propensity would be maintained in the binary feedback condition. Similarly, participants receiving binary feedback first would receive less information than those in the Spatial feedback. So, another prediction would be that a shift from binary to spatial feedback would lead to less risk seeking behaviour and a gradual increase in risk taking while subsequently receiving spatial feedback.

Having defined the potential of information to impact on choice selection, let’s consider how this feedback might also impact on participants abilities to correct errors. Receiving information on how to correct an error is more effective than just being informed of an error (Kernodle & Carlton, 1992). The details of performance were externally available for those receiving spatial feedback. Since the error was not explicitly given in the binary feedback, participants might depend on their own sensory perceptual information, that was accessible as a consequences of movement being acted (van Vliet & Wulf, 2006). Therefore, the binary feedback might result in participants depending on just intrinsic feedback while correcting their error. Hence, any correction would be the result of proprioceptive information. Since the spatial feedback has more information, it should result in more effective error correction strategies.

The current study aims to address these issues by investigating the combined effect of information via feedback and motor competence on risk propensity. The hypotheses are that: (i) participants performing with their non-preferred hand will be less risk-seeking than those performing with preferred hand; (ii) that the order of feedback presentation will have an effect on risk seeking, whereby participants who receive spatial feedback first will exhibit greater risk seeking (in both Spatial and Binary conditions) than those who received binary feedback first; and (iii) that the spatial feedback condition will exhibit better error correction, than those receiving binary feedback.

5.3 Experiment 6

5.3.1 Sample

A total of 124 participants were recruited to take part in this experiment from the University of Leeds School of Dentistry. Sixty-two people (aged 17-31 years; M: 18.68, SD: 2.62; 35 Female) were asked to perform the task with their preferred hand and 62 people (aged 17-31 years; M:19.41, SD: 2.44, 38 Female) performed the task with their non-preferred hand. The Edinburgh Handedness Inventory (EHI) was used to assess handedness (Oldfield, 1971). One person was classified as left handed (EHI < -40), 23 ambidextrous (-40< EHI<40) and 38 people were right handed (EHI > 40) in the group where participants performed with preferred hand and 3 people were classified as left handed (EHI < -40), 21 ambidextrous (-40< EHI<40) and 37 people were right handed (EHI > 40) in the group where participants performed with the non-preferred hand. All participants reported normal or corrected-to-normal vision. This was an opportunity sample, with participants taking part in the study during their visit on a School of Dentistry application day. Ethical approval was obtained from the local research ethics committee (Reference 271016/MM/216). It is important to note here there are a large amount of ambidextrous participants in the sample (35%) compared to general population (1%) (Rodriguez et al., 2010), which might impact on our motor competence manipulation.

5.3.2 Task

The interceptive timing decision making task has been described in previous chapters in detail and for brevity, only the elements relevant to the experimental manipulations are described here (Figure 2.1). In short, participants were asked to select between two targets of varying size which would they subsequently attempt to intercept, or “hit”, as the target moved across the screen. Selecting and successfully hitting smaller targets yielded more reward than selecting and successfully hitting larger targets. Participants did not receive any reward for missing the selected target.

Participants were exposed to two different types of outcome feedback associated with their interceptions- as in Chapters 2, 3, and 4. In the “binary” feedback condition, participants were informed only whether they hit or miss the target at the end of a movement towards the target without any other visual clue about their performance. In the “spatial” condition, participants could see both the end point of the reach and its relationship to the target. All participants were exposed to both feedback conditions, but the order was altered depending on the condition they were assigned to.

5.3.2.1 Reward Schedule

The reward schedule adopted here has been described in Chapters 2, 3, and 4. Feedback was predetermined based on the same principles. (Figure 3.7). In brief, the hit probability and reward functions were manipulated accordingly target size for each target, such that the expected value was matched in every trial and kept constant throughout the experiment. Risk was operationally defined based on the probability of hitting the target. The low probability of hitting the target was less likely to hit, therefore, it was accepted as risky target. The target with less probability of hitting than the other is the risky target because it was less likely to be achieved compared to the other target. The participant received the associated reward value on hit trials, whereas, no points were rewarded on the miss trials. Target location was counterbalanced. Target pairs were randomly displayed based on same reward schedule for all participants.

5.3.2.2 Subjective Measures

Participants were asked to complete a post-experiment survey at the end of the experimental session. The survey (using a 7-point Likert scale; where 1 is totally disagree and 7 is totally agree) required participants to answer how much they agree with the following three statements: (i) “I felt in control of the outcome of the task”; (ii) “I was risk-seeking during the task”; and (iii) “The game tracked my movements accurately.”

5.3.3 Study Design

Previously, the manipulation of using preferred or non-preferred hand resulted in an effect on choice behaviour. In the current study, this manipulation was applied between subjects to avoid transferring the effect in a within subject design. Participants either used their preferred hand or non-preferred hand (two independent groups). All participants received spatial and binary feedback across the experiment, but the order of this feedback was counterbalanced across participants: the Spatial First group was given spatial feedback in the first block (50 trials), followed by binary feedback in the second/last block (50 trials); the Binary First group received Binary feedback first and then Spatial feedback. All participants completed 100 trials in total.

5.3.4 Statistical Analysis

5.3.4.1 Preliminary Analysis

To ensure that there were no systematic age biases that could impact on the results, the age differences for the two independent groups (preferred hand and non-preferred hand) was tested via a t-test. Participant responses from the post-experiment survey, designed to examine subjective measures of riskiness and control were compared using a t-test; or non-parametric 2- group Mann-Whitney U Test if the assumptions of parametric tests were violated. The equality of variance was tested and assumptions of normality were examined by using a Shapiro-Wilk Normality test.

5.3.4.2 Risk Propensity Analyses

To investigate riskiness behaviour throughout the experiment, a 2 (feedback; spatial, binary) by 2 (order; Binary first, Spatial first) by 2 (hand; preferred hand, non-preferred hand) mixed ANOVA was computed. The Levene's test was used to assess for homogeneity of variance. The *ezANOVA* package in R was used to perform this analysis. Bonferroni correction was used for pairwise t test for post-hoc. The generalized Eta-Squared (η_G^2) measure of effect size (Bakeman, 2005) is reported here. Mauchly's Test of Sphericity was used to indicate if the assumption of sphericity had been violated for repeated measure ANOVAs.

To visualise choice selection over time, risk propensity scores were calculated through moving averages with a step-size of 10 trials, where the scores were lagged by 10 trials. As with the global risk propensity measure, a safe choice was attributed a score of 0 and a risky choice was attributed a score of 1. Therefore, higher scores indicate highly risky behaviour, scores of 0 indicate highly risk averse behaviour and 0.5 indicates a risk neutral profile. These scores for individuals were averaged across participants to produce an average measure of risk across the trials.

5.3.4.3 Error Correction

As described in previous chapters, error correction was calculated by subtracting the last shown spatial error from the spatial error in the given trial for both spatial and binary feedback. Linear models were fitted to the data (with better fits indicating more error correction) and compared across conditions.

5.3.4.4 Switch Selection Behaviour Analyses

Switching behaviour as described in previous chapters was considered as switching target from safe to risky or risky to safe based on the outcomes (miss and hit) and feedback type (spatial and binary).

5.4 Results

5.4.1 Preliminary analyses

There was no difference in the ages of participants in our two groups (t(122.64) = 1.61, p = 0.111). An independent t test also showed that there were no significant differences between two groups in measures of control (M = 3.71, SD= 1.73, SE= 0.22 for preffered hand; M = 3.94, SD= 1.55, SE= 0.20 for non-preferred hand), as captured by the post-experiment survey (t(124) = 0.759, p = 0.449; W= 1831, p =0.448). Similarly, there was no significant difference between two groups (t(124) = 1.121, p = 0.264; W = 1806, p = 0.377) in their subjective measures of riskiness (M = 3.67, SD= 1.51, SE= 0.19 for preffered hand; M = 3.98, SD= 1.66, SE= 0.21 for non-preferred hand) on the task.

5.4.2 Primary Analyses

5.4.2.1 Risk Propensity

A 2(feedback type; spatial, binary) X 2(used hand; preferred hand, non-preferred hand) X 2 (order; spatial first, binary first) ANOVA was conducted. There was a main effect of feedback [F(1,122)= 7.763, p = 0.006, η^2_G = 0.017], with higher rates of riskiness in the spatial feedback condition (M=0.63, SD=0.32, SE=0.03) relative to the binary feedback condition (M=0.55, SD=0.31, SE=0.03; p = 0.045).

In addition to this main effect, there was an Order x Feedback interaction [F(1,122)= 6.012, p = 0.016, η^2_G = 0.013] (Figure 5.1) and we also observed a Hand X order interaction [F(1,122)= 6.184, p = 0.014, η^2_G = 0.035] (Figure 5.2). Participants who received binary feedback first were more likely (p=0.009) to be riskier in the Spatial feedback (M=0.63, SD=0.34, SE=0.04) than in the binary feedback (M=0.48, SD=0.29, SE=0.04). In contrast, when participants received spatial feedback first, there was no difference (p=0.86) in riskiness in the spatial (M=0.62, SD=0.29, SE=0.04) and binary feedback conditions (M=0.61, SD=0.31, SE=0.04).

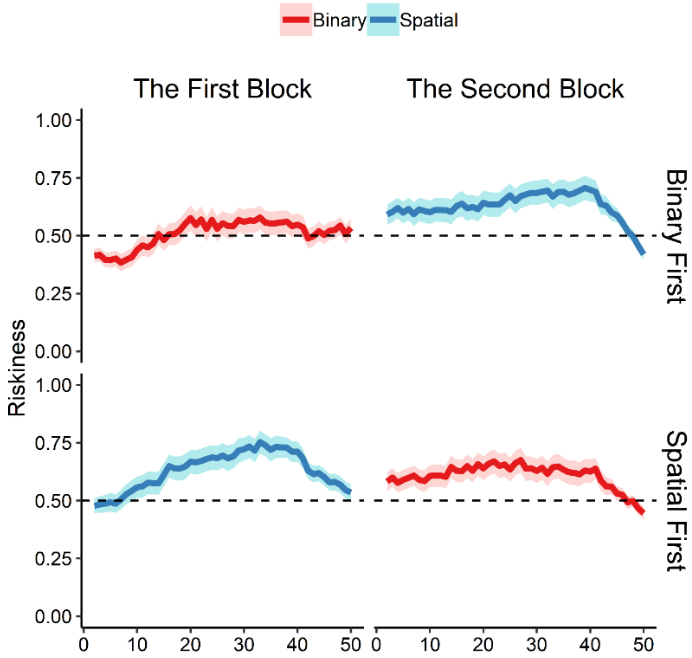

Figure 5.1 Riskiness as a function of Feedback and Task Order. Participants who received binary feedback first became more risk seeking in the second phase of the experiment when spatial feedback was provided. However, when participants received spatial feedback, risk propensity remained consistent across the experiment. The lines show the group mean of moving average and the shaded areas indicate (+) and (-) standard error.

Important for our experiment manipulation, we found that there was no difference (p=0.22) in riskiness for completing the task with the preferred hand (M=0.60, SD=0.27, SE=0.05) and non-preferred hand (M=0.52, SD=0.27, SE=0.05) when participants received binary feedback first. However, when participants completed the task with spatial feedback first with their preferred hand (M=0.69, SD=0.22, SE=0.04), there were significantly more risky (p=0.02) than when they were exposed to binary feedback (M=0.54, SD=0.28, SE=0.05), thus conceptually replicating the results reported in previous chapters showing feedback modulates risk taking.

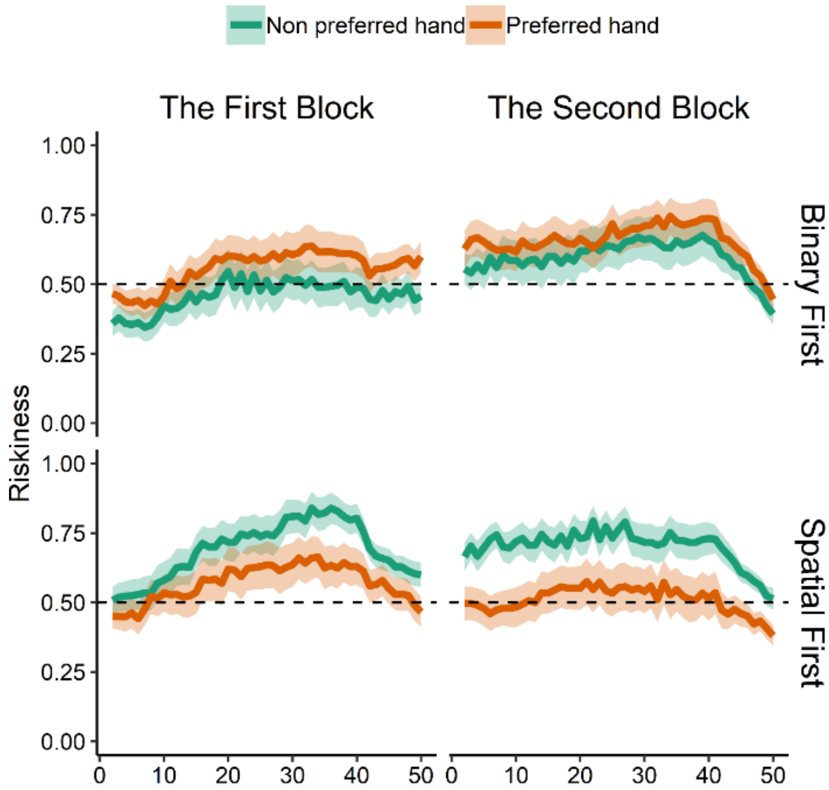

Figure 5.2 Riskiness as a function of Hand and Task Order. Participants performing with the non-preferred hand were more risk-seeking than participants performing with the preferred hand when they both received binary feedback first. Interestingly, this pattern was reversed when participants received spatial feedback first. The lines were generated by using riskiness mean of moving average and the shaded regions indicate standard error.

Lastly, same analysis was run on data from participants whose handedness were measured 100 Edinbrugh Handeness Inventory (EHI) (see Appendix 2).

5.4.2.2 Error Correction

The fitted linear models from data points of two groups are represented in the Figure 5.3. The models were compared within groups (see parameters in Table 9).

The linear model for the binary feedback condition showed a small value for the slope suggesting that the model is skewed from the idealised error correction model. In contrast, the linear model for spatial feedback was very close to the ideal error correction model. The pairwise comparison between two models showed that these two models were significantly different ($t(5861)= 15.788$, $p<.0001$). The same pattern was found in the

Spatial first group ($t(5903)= 14.841$, $p<.0001$) where the spatial feedback resulted in more ideal error correction than the binary feedback.

Table 9 The results of fitted linear model for each condition

Order	Feedback type	ß	df	Lower confidence level interval	Upper confidence level interval
Binary First	Binary	-0.246	5861	-0.272	-0.221
	Spatial	-0.669	5861	-0.715	-0.623
Spatial First	Binary	-0.251	5905	-0.278	-0.223
	Spatial	-0.652	5905	-0.697	-0.606

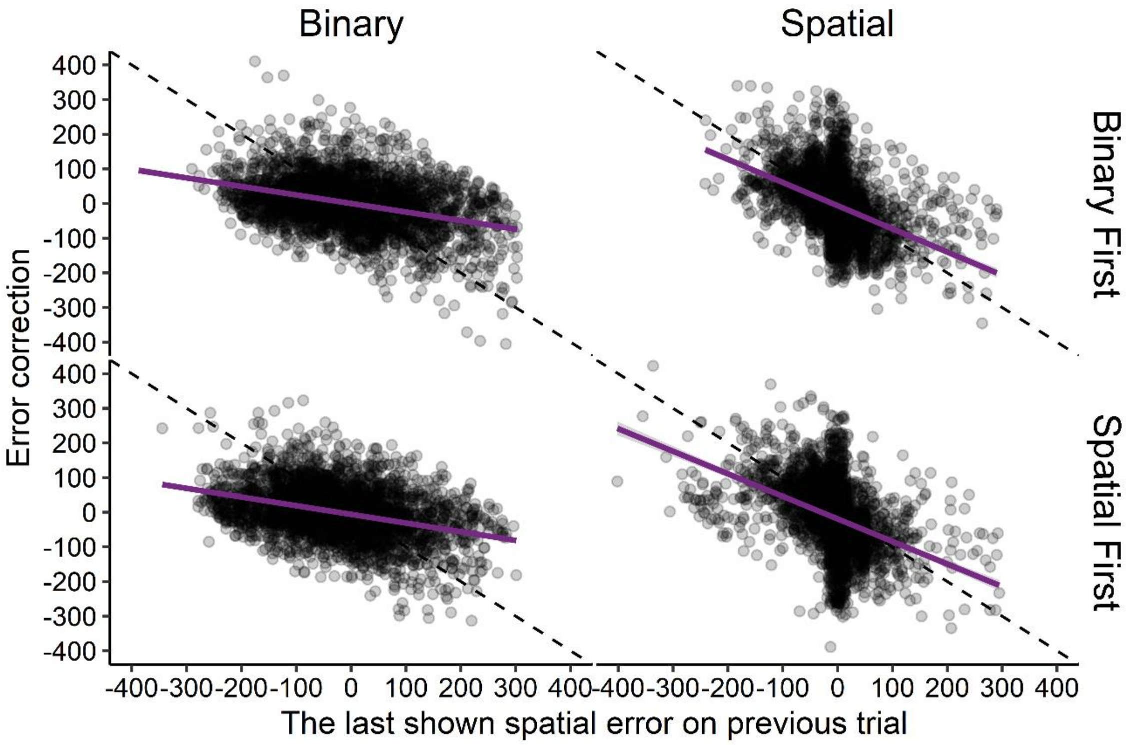

Figure 5.3 Error correction following feedback on the previous trial. On the x axis, the value of last seen spatial error (mm). On the y axis, the differences between their last seen spatial error value and their current spatial error value (mm). An ideal person who would correct the error accordingly has been shown as dotted lines in the graphs. In the graph participants purple line in the spatial feedback shows that the linear model of participants' correction approaches the ideal error correction in the Spatial first and binary first group. However, the linear model in the binary feedback condition does not present a well-adjusted error correction for both groups. The point in the graph represents each data points.

5.4.2.3 Switch Selection Behaviour

Finally, we investigated whether people switched from risky options to safe option or vice versa in response to hits and misses at a trial level. A 2 (Feedback type: Spatial vs. Binary) X 2 (Outcome: Miss vs. Hit) X 2 (Previous Choice: Risky vs. Safe) ANOVA repeated measure design was conducted. There was a main effect of previous selection [$F(1,125)= 7.129$, $p = .008$, $\eta_G^2 = 0.018$], with participants more likely to switch if the previous selection was safe (M = 0.37, SD = 0.34, SE = 0.01) compared to when the previous choice was risky (M = 0.28, SD = 0.30, SE = 0.01) ($p<0.0001$) (Figure 5.4B). There was also a main effect of feedback [$F(1,125)= 8.883$, $p = .003$, $\eta_G^2 = 0.005$]. Participants were more likely to switch in the binary feedback condition (M=0.35, SD=0.32, SE: 0.01) relative to the spatial feedback condition (M=0.30, SD=0.32, SE: 0.01; p=0.022; Figure 5.4A).

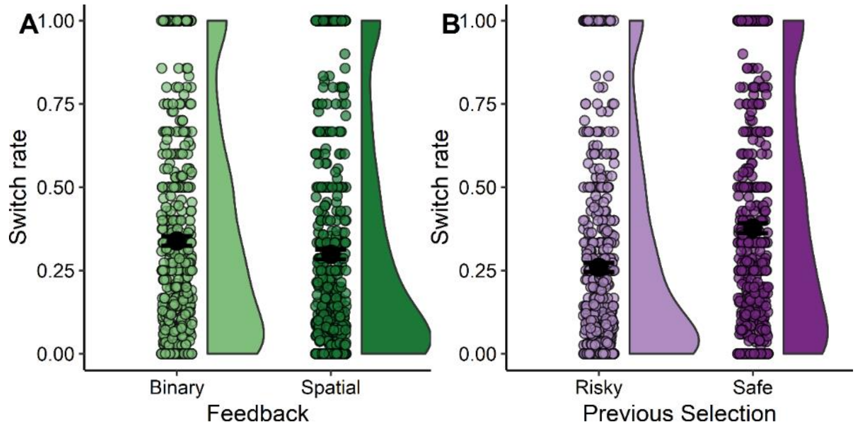

Figure 5.4 Effect of feedback and previous selection on switch rate. Every point represents a mean for a participant. The black points (solid blobs) are group means and lines represent standard error. Participants performing in the Binary feedback (light green) are more likely to switch their previous selection than performing in the Spatial feedback (dark green); participants are also more likely to switch their previous selection after safe selection (dark purple) than risky selection (light purple).

We also observed an interaction between feedback type and previous selection [$F(1,125)= 5.09$, $p = .026$, $\eta^2_G = 0.005$]. Participants in the binary feedback condition showed an equivalent level (p=0.16) of switching behaviour after making a safe choice (M=0.37, SD=0.34, SE=0.02) and risky selection (M=0.33, SD=0.31, SE=0.02), whereas, participants in the Spatial feedback had an increased switch rate after making a safe selection (M=0.37, SD=0.34, SE=0.02) than a risky selection (M=0.24, SD=0.29, SE=0.02; p<0.0001) (Figure 5.5). Notably, there was no interaction for with Outcome (hit and miss) (p<0.395).

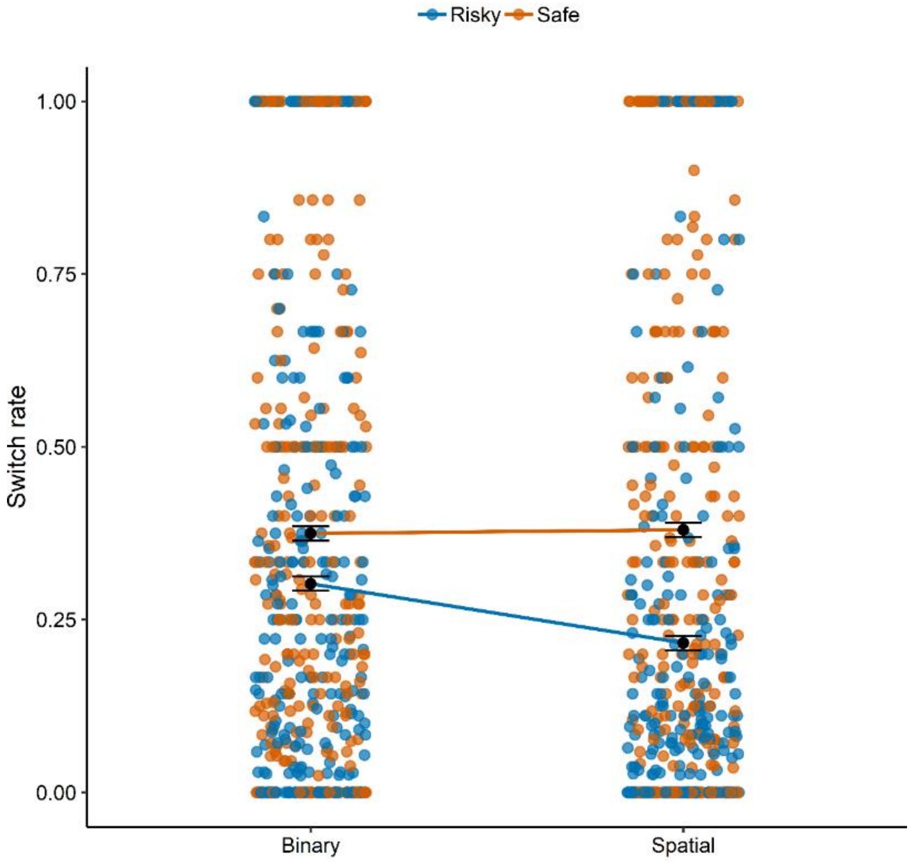

Figure 5.5 Switch Rates as a function of feedback and previous choice. Participants are more likely to switch their selection after a safe selection in both binary and spatial feedback. However, after a risky, choice participants are more likely to change in the Binary than spatial feedback. The points represents ever data points. The black points represent the group mean and black lines represent the standard error.

5.5 Discussion

The present study sought to investigate whether choice selection (and specifically risk propensity) could be influenced by a change in the information provided in the feedback and the order in which the feedback was presented in high and low motor competency conditions. Predicated on previous experiments reported in this thesis and the literature, we predicted that (i) using the non-preferred hand to execute actions would result in less risk-seeking behaviour than using the preferred hand; and (ii) receiving spatial feedback first would heighten risk seeking behaviour relative to the Binary condition. We also sought to explore whether there would be an asymmetry due to the order of feedback was presented.

Contrary to results reported in Chapter 4, our first hypothesis was not supported, but did reveal a nuanced relationship between competency and feedback. The impact of handedness was modulated by the order in which feedback was presented. Specifically, participants performing with their non-preferred hand adopted more risk-seeking behaviour when spatial feedback was received first; whereas, the participants performing with their preferred hand adopted more risk-seeking behaviour when binary feedback was received first. However, we note Experiment 4 in Chapter 4 found binary feedback resulted in more risky decisions than spatial feedback in both the preferred and non-preferred hand.

When examining the impact of feedback format, participants who received spatial feedback first had a higher riskiness score and maintained the high riskiness in the second phase when binary feedback was given. In other words, we found an asymmetrical impact of feedback on choice selection. Participants who received the spatial feedback first showed heightened risk seeking behaviour relative to the binary feedback group - a pattern that has been replicated several times throughout this thesis (Chapter 3.2

(Experiment 2), Chapter 3.3 (Experiment 3), Chapter 4.2 (Experiment 4)). However, what was most interesting in this experiment was the impact of information carry-over. Participants who experienced spatial feedback first maintained their level of riskiness even when they received binary feedback later in the experiment. In contrast, participants receiving binary feedback first showed relatively neutral behaviour on average in the binary feedback condition and then gradually became more risk seeking in the spatial feedback condition (as expected).

It seems clear that there was an information carry-over effect in our group transitioning from spatial to binary. But why might this be the case? We proposed that amount of information received in the early phase of the experiment for this group may have modulated the internal model of the agent causing them to remain risk seeking for the rest of the trials. This shift from exploration to exploitation behaviour is often seen in multi-trial decision-making tasks, where agents seek out information about the task parameters before they start exploiting the environment for reward (Gonzalez & Dutt, 2011; Mehlhorn et al., 2015; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012). Such an interpretation aligns extremely well with the data observed here – participants were able to exploit only because the environment (presentation of spatial feedback) they previously interacted with allowed them to accumulate sufficient information that they could utilise in an information impoverished environment (the binary feedback condition).

We may also consider these results from the opposite end of the same spectrum- that of uncertainty.

Turning now to the experimental evidence on the effect of using preferred and non-preferred hand, participants using their non-preferred hand were more risk-seeking than people using their preferred hand when both groups received the spatial feedback first; whereas, when both groups received binary feedback first, participants using preferred hand had equivalent risk propensity with participants using their non-preferred hand. The differences in these results may be the effect of motor competent derived from using non-preferred hand on risk propensity. The literature suggests that non-preferred hand had more motor noise in the execution compared with preferred hand (Annett et al., 1979; Harris & Wolpert, 1998), which subsequently might mean that people are less competent while using non-preferred hand. McDougle et al. (2018) provided some evidence, in the study conducted on patients who have cerebellar degeneration, that less motor competent might moderate risk propensity where participants have bias towards risk-averse action selection compared to healthy sample (no-motor disease history). In the current study, it is important to note here that receiving an execution error (spatial feedback) resulted in more risk-seeking selections, when compared with receiving only success and failure feedback (binary feedback) in the current study, as was expected. Even considering the higher amount of motor noise whilst performing the task with the non-preferred hand (Annett et al., 1979; Harris & Wolpert, 1998), this might not have been a sufficient increase in motor noise to impact motor competence due to ambidexterity.

Interestingly, for participants using their preferred hand, the risk propensity in the first 50 trials for both the spatial and binary feedback seems to show a similar trend. However, after switching, the participants became riskier when then receiving spatial feedback (binary first condition) and maintained an equivalent risk propensity when then receiving binary feedback (spatial first condition). This highlights the importance of *when* the more informative feedback was presented. Participants seemed to be more risk-seeking when they receive more informative feedback first.

Conversely, participants using their non-preferred hand showed different risk propensity between spatial and binary feedback groups in the first 50 trials. In the first block, participants who received binary feedback first were almost risk neutral in in this condition; whereas, those who received spatial feedback first were risk seekers, as was expected. Then in the second block, the participants who switched from receiving binary feedback (binary to spatial) began to adopt more risk seeking strategies; whereas, those who switched to binary feedback (from spatial feedback) kept a similar level of risk seeking behaviour in the second block to their first block, which was high already. Although participants who received binary feedback then spatial feedback became more risk seeking during the spatial feedback regime, they are less risk seeking than those who received spatial feedback first. This difference is as was expected due to the difference in the feedback provided. Additionally, participants using their non-preferred hand showed relatively riskier behaviour in their second 50 trials, after switching feedback type, showing a different trend to the participants using their preferred hand. This difference may be due to the interaction between feedback type and which the hand is used. Binary feedback might be more beneficial for those using the non-preferred hand (Duff & Sainburg, 2007; Sainburg & Kalakanis, 2017). Interestingly, where participants performed with their non-preferred hand, changes in the information given in the feedback affected the risk propensity more or less in the same direction as for the preferred hand group.

There is one important limitation in the current study that is noteworthy. This sample included a large proportion of ambidextrous people (35%)- which is much larger than the general population (1%) (Rodriguez et al., 2010). We had an opportunity to recruit a large amount of participants from the School of Dentistry and the participants sampled may not be reflective of the general population. Dentistry is an ambidextrous profession (Arora & Saiya, 2018), requiring the skilled use of both hands and our sample, although not professional dentists, may already have had far more experience of using their non-preferred hand than the general population (Kriz, Voola, & Yuksel, 2014).

This may have impacted on the results in at least two different ways. The first possibility is that the manipulation of motor competence might have failed. There was no test conducted to check whether the manipulation of motor competence was achieved. For example, in retrospect, a post-experiment subjective report could have been implemented and participants might have been asked how competent they felt while using their preferred and non-preferred hand. The second limitation is that ambidextrous participants might have received different degrees of sensory information whilst performing the motor task (we had reasoned that the non-preferred hand would exhibit more internally generated motor noise, but this might not have been the case for ambidextrous people). This might have contaminated the results of the current study. Future work could explore this relationship in more detail.

In summary, this experiment has shown that both feedback and competency can together impact on risk taking. The specific impact of these conditions seem to be modulated by the order in which participants experience the different feedback conditions. Participants who receive spatial feedback first have higher riskiness scores and maintained their higher riskiness in the second phase, when compared with the participants who received binary feedback first. The participants who received binary feedback first, became gradually more risk seeking when spatial feedback was subsequently given. The competency of the hand used whilst performing the task was also a factor: participants performing with their non-preferred hand adopted more risk-seeking behaviour when spatial feedback was received first; whereas, the participants performing with their preferred hand adopted more risk-seeking behaviour when binary feedback was received first. Together, these results indicate the importance of prior information received on future risk propensity and the effect of motor noise derived from using non-preferred hand on risk propensity.

Chapter 6 General Discussion

6.1 Overview

Research on decision-making has historically focussed on action selection, with intense examination of the processes that result in choosing one option out of a number of possibilities (Newell et al., 2015). This body of work has been heavily influenced, and has influenced, economic choice theory. In parallel, there has been a large body of work on the processes involved in sensorimotor execution- that is, the implementation of a chosen course of actions to interact with the world (Kording & Wolpert, 2004; Wolpert & Landy, 2012). This stream of work has, until recently, had very little to do with classic decision-making research and only in the last decade have researchers considered framing such behaviours as a form of decision-making (Trommershäuser et al., 2008; Wolpert & Landy, 2012).

The lack of connection between research on action selection and execution is a rather surprising gap given that there can be no decision without execution. This gap is even more remarkable given recent seminal studies have showed a profound impact on choice selection when the contribution of the sensorimotor domain in action execution is manipulated (Green et al., 2010; Parvin et al., 2018). Predicated on these recent experiments and a growing perspective in psychological research in general that human cognition is far more embodied than traditional approaches have considered (Lakoff & Johnson, 1980), this thesis set out to examine the factors that impact on action selection and action execution in determining decision making.

To address this research question, a novel decision-making task was created. The task was designed to examine how individuals maximised reward across different experimental manipulations designed to probe the impact of selection and execution on decision making. A brief summary of the experimental results from these manipulations is presented below before we delve into more general conclusions that may be derived from this work.

6.2 A Brief Review of the Experimental Findings

The experimental work in this thesis started off by examining the effect of agency on risk taking and provided some evidence that being in control of the action execution phase (along with the order with which the feedback was presented) impacts on risk propensity. Being in control of execution in a novel environment, as soon as the task started, resulted in a risk-averse behaviour; whereas, being in control of the execution after not having control of the execution in the first two blocks resulted in more risk-seeking selection. Interestingly, this effect did not hold in a condition where there was no control or only partial control of the execution. Being able to be in control of the execution seemed to be an elegant way to manipulate the sense of agency; however, the literature suggested that positive feedback might be more effective at making people think that they are in control, rather than being actual in control (Wen et al., 2015). Nevertheless, executing an action and being in complete control seemed to influence risk propensity, when compared with none and partial control of the execution, regardless of the different feedback types.

This work was followed by two experiments in Chapter 3 which examined if risk propensity could be modulated by the degree of information provided about execution error in a motor decision making task. To investigate this, two different feedback types were employed. These feedback types were classified based on the information they provided to the agent: knowledge of result and knowledge of performance. The feedback categorised as knowledge of performance (spatial feedback) included the information of the motor execution error; how far the participants were to success. The feedback qualified as knowledge of result (binary feedback) had only one type of information, either failure or success. Importantly, spatial feedback has more information than binary feedback. The result provided evidence that participants receiving spatial feedback were more likely to be risk seeking than those receiving binary feedback; in addition, spatial feedback resulted in higher hit rates than binary feedback. To tackle the influence of differences in hit rate, the expected value needed to be constant for both binary and spatial feedback as in experiment 5. Interestingly, still participants who received spatial feedback still adopted more risk seeking strategies than those who received binary feedback. In both experiments the spatial feedback resulted in better error correction than binary feedback.

Chapter 4 attempted to investigate the effect of motor competence on risk propensity through two experiments. The first study aimed to investigate how different types of feedback had an effect on risk propensity when motor competence was low. To this end, participants were asked to perform the task with their non-preferred hand. The previously used feedback manipulations were also employed in this study. Surprisingly, there was no significant difference in risk propensity between preferred and non-preferred hand. The analyses showed a significant effect of feedback type, where spatial resulted in more risk seeking behaviour. In a second study we investigated if there would be an information transfer effect when switching from using the preferred hand to the non-preferred hand and vice versa. Participants who used their non-preferred hand first were more risk seeking in the binary feedback condition than the participants in the Spatial feedback condition. However, after switching hand the participants in the Spatial feedback condition became as much risk seeking as the participants in the Binary feedback condition. Statistically this interaction was only marginally significant. The literature suggests there might be differences in how the preferred hand and non-preferred hand might use different types of feedback effectively (Renault, 2018; Sainburg, 2002): visual feedback may be more advantageous for the preferred hand, and proprioceptive feedback might be more advantageous for the non-preferred hand and this may manifest in differences in choice selection. In both experiments spatial feedback resulted in better error correction than binary feedback.

The final experimental chapter examined the effect of the prior information generated from different feedback types on risk propensity. The study provided some evidence that receiving spatial feedback first resulted in an equivalently high-risk seeking strategy in the subsequent binary feedback condition. However, receiving binary feedback first did not indicate a similar trend; instead, there was a gradual increase in risk seeking selections in the second block where the spatial feedback was given. Interestingly, the participants performing with their non-preferred hand selected more risky targets, in both spatial and binary feedback, when spatial feedback was given first. It should be noted however, that the sample in this study had far more ambidextrous people than the average population, which might have impacted on risk propensity in an unexpected way. Lastly the spatial feedback consistently has resulted in better error correction than binary feedback in all experiment it has been analysed.

6.3 Common Themes and Implications

Throughout this thesis, some patterns of results were replicated consistently across several experiments. For example, we found a very strong effect of feedback on risk seeking behaviour across most of the experiments in this thesis. Given that outcome feedback is an important source of information to help refine one’s actions to optimise behaviour for a task, it is not surprising to find that this had a profound effect on participants risk propensity. A second common theme was the observation that participants often shifted towards a risk seeking state from their starting position, but that this was generally bounded by some ceiling level of riskiness. These results indicate that participants were performing explore- exploit trade-offs in their decision-making (Gonzalez & Dutt, 2011; Mehlhorn et al., 2015; Mulder et al., 2012; on exploration and exploitation here), accumulating evidence by exploring the task space and exploiting (i.e. selecting risky choices) once sufficient amount of information had been accumulated.

The findings from this work also highlight a much broader point that is often neglected in choice selection research. Most economic choices involve one-shot decisions. Take for example the classic Asian disease problem (where participants are asked to imagine a hypothetical scenario in which they must choose between two options for a disease that would kill 600 people - one option could save 200 people while another would have a 1/3 probability of saving all 600 people, but a two-thirds probability of saving no one) or the Ellsberg paradox described in the introductions. In these famous examples, there are no opportunities to learn from the consequences of one's actions and refine one's behaviour for subsequent trials. Instead, participants can only make use of the priors they bring into the task. Experiences of this type may be extremely limited and thus, the priors quite weak and uninformative (how many times has the average psychology participant had to make a life or death decision as in the Asian disease problem?) In contrast, in the motor learning world, tasks involve using extremely well refined actions (e.g. reaching towards a target), which have been honed over a lifetime of experience and require only calibration to the experimental setting.

These differences may also point towards reconciling differences between findings from decision making on cognitive and sensorimotor decision making. It is often said that the former is susceptible to numerous biases (Kahneman et al., 1974; Kahneman & Tversky, 1979) but the sensorimotor system is Bayes optimal. Could it be that this reflects snapshots of behaviour across very different timescales? This would be an interesting avenue to examine through running extended experiments capturing learning in the laboratory so that the cognitive tasks also become well honed. Alternatively, it may be instructive to look at the developmental trajectory of risk propensity in these tasks, reasoning that very young children should have less experience of interacting with the environment and thus less precise priors and thus optimality of the sensorimotor system may be compromised.

6.4 Limitations and Future Work

We must also consider some of the limitations of the present studies and the avenues that the present work presents for future research.

We took an opportunistic approach to sampling participants for the majority of the studies reported in this thesis. Specifically, we had a unique opportunity to collect data from highly motivated students who presented at the university as part of an interview day for dental undergraduate degree. The remainder of participants were motivated through financial remuneration. Whilst studies have shown that providing financial incentives can have a substantial impact on the ways in which people process outcomes. However, it is plausible to assume that the sample selected for this study were even more motivated than those provided with financial remuneration.

A lab-based task was chosen over real-world and more ‘realistic’ task scenarios so that the component parts of decision-making could be easily separated and manipulated. It would be interesting to see the extent that the behavioural patterns observed here would carry over to different scenarios and more ecologically relevant contexts. Perhaps the most common behavioural strategy throughout the experiments in this thesis was heightened risk propensity when participants received information about their execution error. One explanation for this phenomenon (as explored in Chapter 2 in experimental manipulations on agency and proposed by McDougle et al., 2016; Parvin et al., 2018; McDougle et al., 2019) is that the heightened motor demands of this action induced a sense of control (c.f. pressing a button on a keypad) that manifested in this risk profile. However, it is worth considering that participants only performed a very simple motor action (swipe from the bottom of a tablet to the top on the tablet using a stylus). Naturally, even though swiping is a more “complex movement” than pressing a key (and it is a movement people apply in real-world while using technological gadget like smart phones and tablets), future tasks could examine even more “complex” real world movement, which could provide the context that enable us to do many different movements whilst demanding just one (Janemalm, Quennerstedt, & Barker, 2018). This movement might be converted into a real-life scenario, such as swinging a baseball or cricket bat.

Given that the task properties used in most of the studies in the thesis were set to the equivalent expected value (~37 for each target) between trials in all experiments where hit rate was predetermined, replicating these studies with extremely high and extremely low expected values would be an interesting for future research. Changing the magnitude of the EV (and thus heightening [or lowering] the importance of a given choice) could have a profound effect on choice selection. For example, the decision of which job to take (a high magnitude event) would likely cause different choice strategies than deciding what to cook for lunch (Botella, Narváez, Martínez-Molina, Rubio, & Santacreu, 2008).

One interesting effect found in this thesis was that of motor competence on risk seeking behaviour. Experiments in Chapter 4 that studied motor competence failed to take motor competence measure into account; since, experiments which have studied motor competence have used pathological samples which do not require a measurement (McDougle et al., 2016). In retrospect, the experiment presented in Chapter 5 could have been improved to measure motor competence; however, the feasibility of applying a motor competence battery (Sigmundsson, Lorås, & Haga, 2016) was low due to the time constriction the participants had to perform the tasks. Given the limitations that were taken into consideration, the studies in Chapter 4 and 5 failed to eliminate the effect of confounding ambidexterity. For future studies, this might be an important point to consider.

6.5 Concluding Remarks

Together, these studies demonstrate the importance of looking at the decision-making process as an interconnected whole- one that comprises action selection and action execution. This thesis has introduced a multi-stage multi-trial decision-making task that allows one to manipulate these elements in a controlled manner. Over a series of experimental investigations, we have demonstrated that information manipulation (through constraining actions and feedback and increasing sensorimotor noise) modulates the rate at which participants shift from a risk averse state to a risk seeking state. More generally, these experimental investigations have demonstrated the interplay between cognitive and sensorimotor systems in choice selection by illustrating the bilateral relationship between parameters driving action selection and execution interact to manifest in decision-making.

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APPENDIX A

Supplementary Result For Experiment 5

To investigate the effect of motor competence on decision making, experiment 5 was conducted. High motor competence was operationalised as using preferred hand and low motor competence was operationalised as using non-preferred hand. However, handedness of participants in experiment 5 was ranged between left with 60 EHI score and right hand with 100 EHI , some participants were classified as ambidextrious. This might change the effect of motor competence. Therefore, in these analyses participants only whose handedness were assessed as 100% right or left handed. There are 12 participants (8 female) with 100% right hand Edinburgh handedness inventory score. Therefore this analyses was tested only on these participants.

A 2(feedback type; spatial, binary) X 2(order; preferred hand first, non-preferred hand first) X 2 (used hand; preferred hand, non-preferred hand) ANOVA was conducted. There were not main effects of feedback, order nor used hand. However, there was an interaction between used hand and order [$F(1,8)= 6.812$, $p = 0.031$, $\eta_G^2 = 0.023$]. Pairwise comparisions indicated that there was a significant differences between order (p=0.000) whilist no significant differences in used hand (p=0.16). (see Table 10 for mean values).

Table 10 Value of means, standard deviations and standard errors.

Order	Used Hand	Mean	sd	se
NPH First	PH	0.77	0.42	0.02
	NPH	0.65	0.48	0.03
PH First	PH	0.55	0.50	0.03
	NPH	0.64	0.48	0.03

APPENDIX B

Supplementary Result For Experiment 6

Since participants using both hand might result in some unclearity on the result. Same analysis in the chapter was run on data from participants with 100 EHI score. There were 16 participants (8 Female), 6 using non-preferred hand (left) and 10 using preferred hand while performing.

A 2(feedback type; spatial, binary) X 2(order; spatial first, binary first) X 2 (used hand; preferred hand, non-preferred hand) ANOVA was conducted. There were main effect of used hand [$F(1,12)= 17.054$, $p = 0.001$, $\eta_G^2 = 0.384$]. Pairwise comparisions indicated that there was a significant differences between participants using preferred hand ($M = 0.47$, $SD= 0.50$, $SE =0.02$) and non-preferred hand ($M= 0.85$, $SD= 0.36$, $SE= 0.01$) ($p=0.000$).