UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL AND HUMAN SCIENCES

School of Psychology

A TYPE-2 SIGNAL DETECTION ANALYSIS OF GAMBLING BEHAVIOUR: COGNITIONS, METACOGNITIONS, EXPERTISE AND OPTIMALITY

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ABSTRACT

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Cognitive gambling research has focused mainly on the irrational beliefs and cognitive biases that differentiate problem (PGs) and non-problem (RGs) gamblers. Whilst this research has been informative by highlighting that greater irrational beliefs are associated with gambling severity, the research has failed to determine cause and effect. This thesis proposes that metacognition is an area that may play a central role in the development and/or maintenance of problem gambling. Type-2 Signal Detection Theory (SDT) was used to analyse the data to measure three cognitive and metacognitive components of gambling performance: accuracy, resolution (metacognitive monitoring) and gambling criterion (metacognitive control). Optimality of gambling decisions was also explored. Experiment 1 used a simplified blackjack task, which demonstrated resolution differences between non-gamblers (NGs) and RGs. Experiments 2 to 5 examined the transference of gambling expertise of RGs and NGs in a novel dice gambling task. Experiment 6 demonstrated that the type of task can account for some cognitive and metacognitive variation observed between PGs and RGs, but impaired gambling criterion setting is a pertinent component of PGs' gambling performance that is not dependent on gambling task. Finally, Experiment 7 showed that feedback enables participants to effectively shift gambling criteria to a more optimal position - and may have considerable implications for the treatment of problem gambling. The results are discussed in relation to four specific research questions and underscore the relative contribution of using a SDT approach in the study of gambling behaviour.

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DECLARATION OF AUTHORSHIP

I, Sara E. Carr[1], declare that the thesis entitled

A TYPE-2 SIGNAL DETECTION ANALYSIS OF GAMBLING BEHAVIOUR: COGNITIONS, METACOGNITIONS, EXPERTISE AND OPTIMALITY

and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research.

I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
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- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
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CHAPTER 1
INTRODUCTION

> The gambler is apparently the last optimist; he is a creature totally unmoved by experience. His belief in ultimate success cannot be shattered by financial loss, however great. He did not win today? So what? Tomorrow he will be lucky. He's lost again? It doesn't prove a thing; someday he's bound to win.
>
> (Bergler, 1957, p. 3)

Historically, gambling has been seen as a form of deviant behaviour, often associated with organised crime, antisocial acts, and comorbidity with substance abuse, alcoholism and other addictive behaviours (Breen, Kruedelbach & Walker, 2001), particularly amongst the working classes (Downs, 2008). However, over the past few decades, views on gambling have become increasingly relaxed due to more liberalised governmental approaches. For instance, the introduction of the National Lottery in the U.K. in the 1990s appears to have made a significant impact on social attitudes towards gambling, making gambling for money an increasingly popular and socially acceptable activity (Rogers, 1999).

Seventy-three percent of the UK population participate in some form of gambling each year (British Gambling Prevalence Survey, Wardle et al., 2010). However, despite facing repeated defeats and substantial monetary loss, a minority of gamblers still believe that they will be able to 'beat the house'. It is for these individuals (estimated 1% of the UK population; Wardle et al., 2010) that a preoccupation with gambling develops, which leads to a perpetual 'chasing' of losses, and a lack of control over how much and how often one gambles (Smart & Feris 1994). These behaviours can lead to more serious consequences for the individual, family, and society, such as depression and anxiety disorders, and relationship (Grant & Kim, 2001) and financial strains (Ibanez et al., 2001), sometimes leading to illegal acts to pay off gambling debts.

There has also been a substantial increase of remote gambling opportunities in terms of access to Internet, television and mobile gambling (Griffiths, 2007; Wardle et al., 2007), all of which are difficult to control and monitor. With more recent liberalisation of gambling advertising (Gambling Act, 2005), as well as the possibility of new casinos being built across the UK, and individuals seeking ways of responding to the present economic crisis, it may be reasonable to expect that there will be a corresponding rise of gambling prevalence. With this rise may be an increase in those who exhibit attributes associated with pathological/problem gambling[2] behaviour (Hodgins & Makarchuk, 2003). Indeed, since 2007, there has been a reported increase in problem gamblers in the UK from 300,000 to 450,000 (Wardle et al., 2010).

As the above quote highlights, it may be a lack of self-reflection of their behaviours or thoughts (attributions) that contributes to the development and maintenance of problematic gambling behaviour. Problem gamblers appear to be motivated by a way of reasoning; core beliefs that can persist even when a gambler experiences multiple losses (Griffiths, 1995): if they are successful, the outcome is a product of superstition or 'skill' (Gaboury & Ladouceur, 1989; Toneatto, 1999); if they are unsuccessful, the outcome is attributed to bad luck or idiosyncratic losses (Lau & Russell, 1980).

The purpose of this thesis is to explore how gamblers monitor their decision-making and control their gambling, whilst utilising a unique, objective approach to studying gambling behaviour. By understanding the differences between sub-types of gamblers (both non-problem and problem gamblers) and non-gamblers, a better understanding can be acquired as to *why* some individuals develop problems with gambling, and others do not; a key question for all gambling researchers.

Gambling and Decision-Making Research: An Overview

To date, research into gambling behaviour has revealed various potential risk factors determining whether an individual is at high risk of developing a problem with gambling; however, the research in each area is relatively sparse, and at times inconsistent (Johansson, Grant, Kim, Odlaug & Gotestam, 2008). The research that has been carried out has embraced a diverse range of disciplines, such as economics and sociology (e.g., Eadington, 1999; Walker & Barnett, 1999; Hraba, Mok & Huff, 2005), and anthropology (e.g., Papineau, 2005) to psychology (Blaszczynski, 2000; Nower & Blaszczynski, 2006), among others.

[2] The term 'problem gambling', referred to in this thesis, incorporates both pathological and problem gambling. The former, also known as *compulsive gambling*, is a type of impulse-control disorder and is considered to be the more serious (APA, 1994). However, both may have detrimental repercussions for the individual, family and society.

Problem gambling is a relatively new area of exploration in psychology. Most of the research appears to relate to the early stages of gambling behaviour and focuses primarily on risk-taking, personality and irrational belief theories (Martins, Tavares, Lobo, Galetti & Gentil, 2004). For example, some research has shown that pathological gamblers display elevated traits of impulsivity compared to the general population, and this characteristic may be a risk factor for developing pathological gambling (Myerson & Green, 1995; Vitaro, Ferland, Jacques & Ladouceur, 1998; Nower, Derevensky & Gupta, 2004). Using questionnaires and psychometric measures, Blaszczynski and Steel (1998) investigated the prevalence of personality disorders in pathological gamblers. Their findings suggested that the majority of participants had an average of 4.6 personality disorders, and there appeared to be a correlation between borderline, histrionic and narcissistic personality disorders, gambling behaviour and impulsivity and affective instability.

Moreover, Petry (2001a) explored impulsivity more directly by examining the discounting of delayed rewards in pathological gamblers with and without substance use disorder. The experiment investigated the responses of participants when given the option of a hypothetical larger delayed reward or a smaller immediate reward. Petry (2001a) found that pathological gamblers discounted delayed rewards more rapidly than did the control participants. In addition, her research concluded that pathological gamblers with substance use disorders discounted at an extraordinarily high rate. One explanation for the high comorbidity between substance use disorders and pathological gambling may be that ‘both may be manifestations of an underlying personality trait of impulsivity’ (Petry, 2001b, p. 29).

Supporting the findings that pathological gambling may be a result of an impulse control deficit, Chambers and Potenza (2003) reviewed neurobiological literature that indicated a link between impulsivity and an apparent disturbance in risk-benefit decision-making. A particular focus of the review was on adolescent brain differences in comparison with adults. It was concluded that impulse-promoting substrates operate more robustly in adolescents because their brains are still developing. Further, substrates that inhibit impulsive decisions are not yet maximised in adolescence, which may indicate a biological vulnerability to impulsivity. These findings present biological evidence to support psychological impulsivity research and provide one explanation as to the high prevalence of pathological gambling in adolescence (Hardoon, Gupta & Derevensky, 2004).

Although the impulsivity characteristic of problem gamblers is a pertinent find in recent gambling literature, differentiating between degrees of impulsiveness is an area that is still under investigation. Whilst some research reports high levels of impulsivity in pathological gamblers (Steel & Blaszczynski, 1998), other investigations indicate no difference between pathological gamblers' and control groups' impulsiveness (Allcock & Grace, 1988; Dickerson, Hinchy & Fabre, 1987).

Rachlin (2000) provided an alternative theory of gambling behaviour and suggested a 'string theory' whereby problem gamblers unconsciously play in 'rounds' or 'strings' that are separated by wins. In other words, when a win takes place in a 'string' of maybe two or three losses, the win becomes more pertinent. This delayed reinforcement, it is argued, leads to a persistence of gambling behaviour as it creates positive periods of excitement, despite the overall loss of money being more than what the individual is able to win.

Rational Decision-Making?

It was once assumed that decision-making was a systematic, rational process with the evaluation of costs and benefits (Fernald, 1997; Stewart, Chater, Stott & Reimers, 2003). "The mind was likened to an intuitive statistician producing judgements that…are responsive to the variables implied by statistics and probability theory" (Juslin, Winman & Hansson, 2007, p.3), with 'Expected Utility Theory' (EUT) previously being one of the major theories of the analysis of decision-making under risk. EUT advocates that the decision-maker computes each of the uncertain prospects and compares their expected values by multiplying each potential gain by the number of ways it can occur (Bernoulli, 1954; Mongin, 1997). In sum, EUT suggests that people tend to be risk-averse (Tversky & Fox, 1995; Rhoads, 1997), and it may be said that in some predictable choices, when alternatives differ only on one dimension, this preference may be the case (Green & Myerson, 2004).

However, the more general decision-making literature has demonstrated that individuals are loss-averse (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991), suggesting that losses are more heavily weighted than wins when making value-based decisions. Kahneman and Tversky (1979) proposed the 'prospect theory' (PT), whilst discounting EUT. Prospect theory refers to the observation that the prospect of a loss has a greater impact in decision-making than does the prospect of an equivalent gain, and hence suggesting that not all decision-making is logical. In their study, participants were presented with hypothetical problems primarily concerning money or saving lives, and then were asked to make a decision as if they were actually faced with the choice in real life. Specifically, the researchers discussed the 'reflection effect'; which implies that risk-aversive behaviour in the gain domain (for example, when a participant is presented with a problem in which it is possible to gain something) is accompanied by risk-seeking behaviour in the loss domain (for example, when the problem is reversed so it is possible for a participant to lose something). To illustrate, participants were presented with two choices:

A. 80% chance of winning 4,000 (Israeli currency)
B. Definitely win 3,000

Eighty percent of the participants selected the second option, which showed that the majority of participants were risk-averse in the positive domain. When the problem was reversed, so the prospects involved losses rather than gains, ninety-two percent of the participants selected the first option in which they would prefer to take the risk of an 80% chance of losing 4,000 rather then a definitive smaller loss of 3,000, illustrating risk-seeking behaviour in the negative domain. It appears that people tend to choose a certain gain over a larger gain that is merely probable, and prefer a loss that is probable over a certain loss, even if it is significantly smaller. A person's first priority is not to lose, and gaining is secondary to this dynamic. The framing of questions appears to have a large impact on an individual's choice; however, Fong and McCabe (1999) posit that "prospect theory…offers little, if any, prediction of how or why involvement in a process should matter" (p.10927), with McElroy and Seta (2007) arguing that prospect theory fails to consider the involvement of a number of individual and contextual factors. Perhaps research into decision-making in the gambling literature offers some contributions that incorporate both individual and contextual factors.

Irrational Beliefs and Cognitive Distortions

The research on psychological aspects that come into play when an individual is faced with a decision is being explored more thoroughly. Cognitive theories of gambling assume that the core beliefs of the problem gambler are irrationally flawed (Rogers, 1998). Many cognitive researchers share this observation and there is a substantial body of work that has focused on the irrational decision-making processes underpinning problem gambling behaviour (Breen et al., 2001; Gaboury & Ladouceur, 1989; Croson & Sundali, 2005). Confirming Rogers' (1998) findings, this research has shown that many individuals hold erroneous perceptions and irrational beliefs about their gambling behaviour/skill and their personal involvement in gambling activity. For instance, many social gamblers misinterpret their chances of winning, hold false beliefs about randomness and skill, partake in superstitious behaviour and overestimate their control over the games (Bersabe & Arias, 2000; Delfabbro, 2004).

There appear to be three distinct theories of irrational beliefs: the 'illusion of control', the 'gambler's fallacy' and the 'near miss'. Langer (1975) introduced the theory of the 'illusion of control' as a means of studying cognitive bias in gambling. Illusion of control means an expectancy of a winning probability incorrectly higher than the objective probability would warrant; in other words, some individuals treat random events or low-probability events as controllable. As an example, an individual may roll the dice a certain way as a means of controlling the outcome. Some research has supported the view that problem gamblers hold more irrational beliefs of control over the games they play than non-problem gamblers (e.g., Delfabbro, Lahn & Grabosky, 2006; Miller & Currie, 2008; Moore & Ohtsuka, 1998). Interestingly, in a study by Wohl and Enzle (2009) participants were more likely to allow a gambling partner (a confederate) to spin a roulette wheel and bet more money on the outcome of a spin if the participants were influenced to believe their partner was lucky. Similarly, Fong and McCabe (1999) found that participants valued their own lottery tickets more highly than others.

The 'gambler's fallacy' is the belief that two independent events are interrelated: after an event has occurred, the probability of it occurring again is lowered (Rogers, 1998). Citing an example, in terms of lottery play, players may believe that a number drawn the previous week has less chance of being drawn again (Ariyabuddhiphongs & Phengphol, 2008), and the probability of winning increases after a run of losses (an idea that often leads individuals to 'chase' their losses; Rogers, 1998).

Finally, the 'near miss' distortion occurs when unsuccessful outcomes are proximal to the jackpot or a large win. Applied to slot machines, as one example, a near miss may be when two out of three winning symbols on the payout line appear. Research has shown that near misses motivate individuals to bet significantly more money (Cote, Caron, Aubert, Desrochers & Ladouceur, 2003). In addition, studies have indicated that this enhanced motivation may be due to the recruitment of win-related reward circuitry (Clark, Lawrence, Astley-Jones & Gray, 2009).

Walker (1992a) proposes that there are three main flawed beliefs that regular gamblers continually construct: 1) it is possible to make money through gambling; 2) the regular gambler is bound to win in the long run; and 3) persistence will bring reward. In terms of the first belief, it is possible for some individuals to make money through gambling (professionals), but for the average regular gambler, the house most often wins, particularly in games of pure chance such as roulette or slot machines: “at the heart of optimistic bias lies a misunderstanding of chance” (Rogers, 1998, p. 124). In terms of the second and third expected beliefs of the regular gamblers, particularly in relation to games played in the casino (i.e., slot machines, blackjack), these have been designed with odds to have the ‘house’ win more often than the individual players. If slot machines are taken as an example, many people believe that if a machine has not ‘paid out’ in a while, it may be due to pay out any minute; however, slot machine payouts are random events (Turner, 2002). Persistence may mean that reward is achieved, but at the cost of already inserting too much money into the machine with a consequence of winning a small (if any) profit, an issue most often ignored by gamblers.

Turner and Liu (1999) found that as many as 50% of problem gamblers have experienced a large early win and the researchers maintain that these individuals tend to focus on early experiences, particularly experiences that support their beliefs. If someone has had an early win, then his/her future plays will most likely result in distorted expectations. The researchers concluded that problem gamblers tend to have a poorer understanding of random events compared to non-problem gamblers, and suggest that altering these beliefs may help with prevention and/or treatment of problem gambling. In addition, Rogers and Webley (2001) observed that problem gamblers are generally *overconfident* in how much control they have over their gambling in terms of being able to stop whenever they want, their influence over the chances of winning, and, as a means of controlling their finances.

To cite one fairly recent example, Miller and Currie (2008) used prevalence survey data to investigate the relationships between problem gambling and irrational cognitions. The researchers found that not only was there a positive correlation between irrational gambling cognitions and participation in gambling, but individuals engaging in gambling activities also spent a smaller proportion of their income on these activities if they held fewer irrational beliefs.

Whilst there is some support for the role of dysfunctional cognitions in the development and maintenance of pathological gambling, the research findings on irrational beliefs appear to be inconsistent. Some research has found no difference between the perceptions of problem and non-problem gamblers (Ladouceur, 2004; Horton, Turner & Fritz, 2006). And, counter-intuitively, problem gamblers also do not appear to have poorer understanding of objective probabilities (Parke, Griffiths & Parke, 2005; Turner, Zangeneh & Littman-Sharp, 2006).

These observations, however, are challenged by researchers such as Delfabbro et al. (2006) who examined variations in gambling-related cognitions in an adolescent population. They found that problem gamblers were more likely than non-problem gamblers to state irrational beliefs but appear to be no less accurate than others when acknowledging objective and binary odds. From these studies it may be hypothesised that during a gambling task, personally-relevant cognitions, such as control over the situation, and superstitious behaviour, may override the objective probabilities and rationalities, leading to unhealthy gambling behaviour in some individuals.

With a lack of concrete empirical research, preventative and treatment actions have become delayed (Johansson et al., 2008). Wells and Purdon (1999) highlight in their paper that current cognitive literature puts too much emphasis on discovering the content of the gamblers' thoughts and beliefs. The counter argument seems to be that the role of active cognitive processes, such as decision-making, metacognitive monitoring, and strategic regulation, have been restricted in the cognitive gambling domain, and that there may be further opportunities for exploring these research avenues. This assertion resonates in the current literature as studies have attempted to make the study of gambling behaviour more 'scientific', with fewer subjective measures of behaviour (e.g., self-reports, verbal protocols and questionnaires) and has tried to find the causal factors that might explain cognitions or behaviours.

As one example, Roca et al. (2008) examined the brain's executive functioning, associated with the workings of the pre-frontal cortex, which appears to deal with decision-making and other higher-order thought processes. The researchers used a neuropsychological approach to compare the decision-making of pathological gamblers and healthy controls in 'risky' tasks. Findings indicated that pathological gamblers demonstrated an impaired inhibitory control mechanism that resulted in their choosing short-term gains over long-term consequences. Perhaps most significantly, the researchers asserted that this impairment may contribute to a pathological gambling disorder.

Pursuing similar neuropsychological lines of inquiry, Lawrence, Luty, Bogdan, Sahakian and Clark (2009) found that problem gamblers demonstrated a deficit in impulsive decision-making in neuropsychological tests, which mirrored results of alcohol-dependent individuals. Their findings suggest that the impulsive decision-making may not be distinct to problem gambling, but also possibly to other behavioural addictions. Based on this work, one working hypothesis may be that some individuals simply are unable to control their decisions and/or behaviour that perpetuate selective addictive disorders. From the current understanding of gambling behaviour, it is likely that investigating the complexities of decision-making and higher-order thought processing is a logical next step in learning more about the aetiology of gambling.

The Strategic Regulation of Accuracy

Defining Metacognition

One area that has received very little attention in the gambling literature is that of metacognition. Initially rooted in developmental psychology (Millar, 2003), Flavell (1976) was one of the first researchers to describe metacognition as "one's knowledge concerning one's own cognitive processes and products or anything related to them, e.g. the learning-relevant properties of information and data" (p. 232). Flavell's (1979) research concerned the improvement in children's memory abilities as a function of greater conscious understanding of the rules that govern memory and cognition. While Flavell's considerations continue to contribute to our understanding of metacognitive processing, Nelson and Narens (1990) have questioned the validity of his results. In particular, the researchers found a degree of inconsistency between his aims and ideas of monitoring and control.

With a view to reconciling disparate cognitive constructs, Nelson and Narens (1990, 1994) focused on a theory that integrated the meta-level and object-level of cognition through a reciprocal flow of metacognitive monitoring and metacognitive control (see Figure 1.1). Metacognitive monitoring involves evaluative judgements of one's cognitions by analysing what one knows and does not know. It also focuses on establishing how these judgements are enacted in altering one's behaviour, for example, changing learning strategies.

The monitoring and control processes underlying decisions are used in the strategic regulation of accuracy (Goldsmith, Koriat & Weinberg-Eliezer, 2002). When individuals have the option of controlling the information that they report and withhold-such as in a courtroom- they can enhance the accuracy of their reported information (Koriat & Goldsmith, 1996). This control can be utilised optimally if the individuals can effectively discriminate between their correct and incorrect information (monitor). The next sections of this chapter examine how the monitoring and control processes are used in the strategic regulation of memory accuracy, and how this framework may be applied to new contexts, such as gambling.

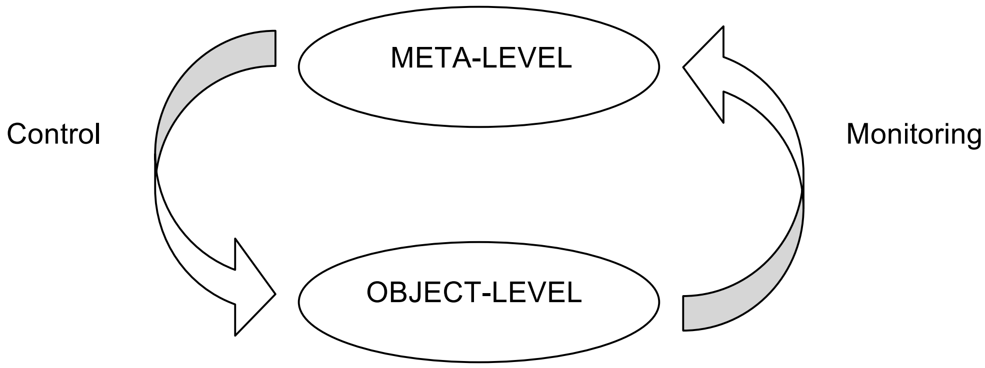

Figure 1.1. A framework of the two separate (but influencing) processes of metacognition (see Nelson and Narens, 1994). The arrows indicate the flow of information. During the monitoring process, the meta-level is informed by the object-level of the present state, and during control, the meta-level modifies the object-level.

The Strategic Regulation of Accuracy in Other Contexts

Contextualising how metacognition relates to the gambling domain may benefit from a brief review of how metacognitive research has developed in the area of memory research.

Although a vast array of memory research has informed psychology since the late 1800s, there is still no consensual framework for understanding the retrieval of memories (Goldsmith & Koriat, 2008). Early investigations were largely dominated by a quantity-oriented "storehouse" metaphor of memory. These studies were frequently grounded in participants recalling external phenomena, such as

Ebbinghaus' (1885) 'scientific' research on counting the number of nonsense syllables that could be retrieved. Later explanations into memory also focused on theories of forgetting by, as one example, asking participants to recall specific items while varying time parameters (e.g., Cowan, 1988; Baddeley & Hitch, 1974).

More recently, there has been a shift from quantity-based investigative approaches towards more holistic or multi-dimensional accuracy-based accounts of memory retrieval (e.g., Koriat & Goldsmith, 1996; Metcalfe, 2000; Higham, 2007). In other words, considering both motivational and scientific aspects related to memory, researchers are now acknowledging the importance of different goals of remembering in everyday life, with growing awareness or recognition that it is crucial to distinguish between the amount of information correctly recalled (accuracy), the extent to which an individual is conscious of what s/he has perceived (monitoring), and how this information is utilised (control).

To clarify the context-memory relationship, it may be helpful to reflect for a moment on a free-recall situation, such as an eyewitness reporting on a criminal event. In these cases it is self-evident that situational factors must be taken into account in deciding on a verdict. From a psychological perspective, a number of cognitive and metacognitive processes are simultaneously at play. In terms of the witness, s/he must a) first decide if the memory is ingrained enough to be able to make a recollection of the event (retrieval); b) successfully differentiate between his/her own correct and incorrect replies (monitoring); and c) decide which information to report (ideally the most accurate), and which pieces of information to withhold to avoid making false statements. This third consideration is the response criterion setting, and, depending on the situation context and the demands of the observers, the criterion will be set at different levels. In the case of the eyewitness at court, the individual will be required to make highly accurate statements, so the response criterion is most likely adjusted upwards (conservative response bias), meaning that the answers reported are accurate, but the amount of information the witness reports is reduced as less certain recollections may be withheld. The witness will most likely not want to report information that he/she is not certain of, as the consequences of being incorrect are too great. In contrast, in the presence of different observers, such as discussing the same robbery event with friends after the trial, the response criterion will most likely be lowered to increase the quantity of the information, as there is not such a high reliance on accuracy (Kelley & Sahakyan, 2003). Thus, an accuracy-quantity trade-off emerges (Goldsmith & Koriat, 2008).

Metacognitive Judgements: Do they Accurately Assess Performance?

An individual's strategic regulation of accuracy is dependent on the ability to monitor self-knowledge (Bjork, 1999). While dissonance between self-regulation of accuracy and judgement can result in source monitoring errors and/or a bias in responses, some studies into the confidence-accuracy relationship have produced contradictory findings (Deffenbacher, 1980; Weingardt, Leonesio & Loftus, 1994; Perfect, 2002). To illustrate, Perfect (2004) observed that in eyewitness memory cases individuals have not had the feedback they would normally receive when answering general knowledge questions, and therefore lack knowledge about their ability to provide evidence. This cognitive gap may infer that their confidence does not match the accuracy of what actually occurred, leading to under- or overconfident performance.

Self-regulation has also been studied in other contexts. Higham (2007), for example, investigated monitoring and criterion setting underlying the strategic regulation of accuracy on formula-scored, multiple-choice tests (Scholastic Aptitude Tests). His findings confirmed that individuals can be significantly over- or underconfident in their responding, depending on the test conditions. Participants were able to significantly shift their response bias between two incentive conditions (low incentive: -0.25 points for an incorrect answer; high incentive: -4 points for an incorrect answer), with fewer answers withheld in the low incentive condition. However, a dichotomy was demonstrated when participants who were allocated to the low incentive condition were shown to be too conservative (underconfident) in their responding; that is, they should have answered more questions than they had done in order to optimise their overall score (see section 'Measuring Metacognition' regarding optimal bias). In contrast, participants in the high incentive condition answered questions too liberally (showing overconfidence). Participants should have withheld more of their responses in this condition to gain better marks on the test. The data implies that participants in this educational setting are not setting their response criterion as effectively as they could, based on the demands of the task, and this constraint may have implications for how different types of students perform. Further, Higham (2007) showed that the questions that were unanswered by the students had a ‘greater-than-chance’ probability of being correct, and proposed that a potential explanation for this finding is evidence for unconscious processing. Participants are not discriminating between their correct and incorrect answers well enough, and this lack of self-knowledge impacts on their regulation of accuracy. Busey, Tunnicliff, Loftus and Loftus (2000) investigated the confidence-accuracy relationship in recognition memory. When participants studied a series of faces in a dimly lit condition, testing in a bright condition reduced recognition accuracy but increased confidence. The researchers concluded that the luminance manipulation had altered the participants’ fluent processing during testing.

Despite many manipulations and real-life examples of the potential lack of validity of metacognitive judgements, investigations have also established that metacognitive judgements can calibrate with recall or performance. Drawing on Judgements of Learning (JOLs) literature, several studies have reported that when learners are presented with the same list of items for several study-test cycles, their JOLs are well calibrated for the first cycle (Dunlosky & Nelson, 1994). Judgements of learning, or metamemory judgements, are made when knowledge is acquired. However, when participants are asked to provide a judgement of how many items they will recall overall, their transformed percentages tend to be substantially lower than item-by-item judgements, yielding underconfidence (Mazzoni & Nelson, 1995).

While inconclusive in fully explicating the validity of metacognitive judgements, there can be little doubt that situational/task demands, and task ‘payoffs’ do affect individuals’ strategic regulation of accuracy.

Manipulating Monitoring and Control

Another substantive question to raise with regard to the metacognitive literature is whether monitoring and control processes operate in the manner that has been theoretically implied. Do these processes interact or do they manifest separately? Indeed, several studies have explored how the effectiveness of monitoring and control processes enhance learning and memory performance, and research has been able to separate and measure the two processes independently (e.g., Experiment 1, Koriat & Goldsmith, 1996).

Koriat and Goldsmith (Experiment 2, 1996) manipulated monitoring effectiveness using different sets of general knowledge items that were mixed into one test. One set had ‘standard’ questions that were expected to produce a generally good level of monitoring in the participants. Moreover, they formulated a 'deceptive' set of questions that were expected to elicit high proportions of incorrect responses. Participants took part in two phases: the first phase concerned involvement in either a recall or recognition version of the test questions under forced-report requiring confidence levels (to assess how well they monitor); while in the second phase, they were required to take the test again under free-report instructions, in which they would gain one point for a reported correct answer but lose one point for a an incorrect answer (to assess their report criterion). The results were as the researchers anticipated; there was a positive relationship between individuals' confidence judgements, with higher levels of accuracy obtained given a free-recall task. Perhaps unsurprisingly, with the deceptive questions, participants' monitoring effectiveness was poor, resulting in low levels of accuracy, despite confidence judgements that were similar to what the standard questions produced. Koriat and Goldsmith (1996) concluded, "free-report memory performance depends on the effective operation of metamemory processes that are simply not tapped by forced-report performance" (p. 506).

Studies on self-regulated learning models in education have shown that accurate metacognitive monitoring will produce more effective regulation, which will in turn produce better performance on a test (Mazzoni, Cornoldi & Marchiteeli, 1990). For instance, when studying for an exam, students with good monitoring skills will know what information they already know and which information they need to revise. In order to do well, they devote more time on the uncertain information and therefore perform well in the exam. In contrast, students with poor monitoring ability may often find it difficult to discriminate between information they know and do not know and find it hard to arrange their study time, likely leading to poor performance on the exam. While the logic behind the latter example appears sound, not all studies have reached this conclusion. For example, in a review by Schneider and Pressley (1997), the researchers deduced that there was no clear evidence of a monitoring-performance relationship in terms of regulating study. Despite this finding, Thiede, Anderson and Therriault (2003) argued that this conclusion might be due to the method used in previous research: the research had not allowed participants to exercise their monitoring by having the chance to regulate their study with a free-recall method, and so accurate monitoring cannot be observed. As monitoring and response criterion are under the participants' control, methodology that allows the participants to differentially allocate study time should produce a relationship between monitoring and performance. To this end, Thiede et al. investigated how differences in metacognitive monitoring affected regulation of learning by instructing participants to generate a list of five keywords that summarised each text (of 6), select the texts for restudy, and they were then retested. Participants were allocated to either a no-keyword (control) group, who were not required to write any keywords; an immediate keyword group, who wrote the keywords immediately after reading each text; or a delayed-keyword group, who wrote the keywords after reading all six texts. Participants were given no training on how to write keywords. After given the instructions, all participants were asked to make an 'ease-of-learning' judgement on a likert scale (1=very difficult; 7=very easy) and state how easily they could learn the information from each passage. After reading the texts and writing the necessary keywords, participants were required to answer six questions to assess their comprehension of each text. By manipulating the generation of keywords, monitoring accuracy could be varied and resulted in good monitoring for the delayed-keyword groups compared to the other groups. This increased monitoring led to more effective regulation of study with significant increases in overall test performance. Thiede and colleagues' research also analysed how participants self-regulated their study, by the correlation between a participants' comprehension rating and whether a text had been selected for restudy. As anticipated, however, participants in the delayed-keyword group were more likely to select less learned texts over better-learned texts compared to the other two groups, indicating that they knew how to regulate their monitoring accuracy more effectively. Son and Metcalfe's (2000) review also conjectured that in 35 out of 46 experimental conditions, when learners are given the freedom to regulate the amount of time spent on each item, they tend to allocate more time to items subjectively judged 'difficult' to learn than those judged 'easy'. Moreover, Metcalfe and Kornell (2003) examined the effectiveness of participants' study time allocation for enhancing memory performance. The results suggest that under self-paced conditions participants' strategies were appropriate to the goals of learning, supporting that they are able to successfully regulate their accuracy.

Some studies have highlighted that participants' monitoring performance can be affected by the goals of the task. For instance, when learners are presented with an easy goal, such as recalling 10 out of 30 items, participants choose to learn the 'easy' items over the 'difficult' items (Thiede & Dunlosky, 1999). Similarly, Son and

Metcalfe (2000) manipulated time pressure to explore how participants' learning would be affected and found that participants under high time pressure allocated most of their restudy time to easier materials. With less time pressure, more time was devoted to difficult test materials.

Another determinant affecting self-regulation relates to the extent of strategic control individuals have over their decision-making. One premise is that individuals are assumed to have little strategic control over the distributions of evidence that are available during recognition testing; however, the response criterion is assumed to be under a high level of strategic control, with individuals being capable of shifting their criteria depending on the task demands, such as the manipulation of different incentives (Han & Dobbins, 2008). For instance, in Koriat and Goldsmith's (1996) first experiment, the researchers found that participants in a high-incentive (penalty) condition set stricter criteria than participants in a moderate-incentive condition.

Furthermore, Kelley and Sahakyan (2003) assessed the role of monitoring and control of two populations: young and old adults in free and forced report conditions of different incentives for accuracy. It was found that the responses in the high incentive for accuracy condition (25 cents gained for each correct answer; $2.50 deducted for each incorrect answer) resulted in a criterion shift (change in control) as the young participants set their response criteria higher to gain greater accuracy, but at a cost of losses in quantity compared to the moderate incentive condition (25 cents gained for each correct answer and the same amount lost for an incorrect answer). Interestingly, older adults did not adjust to the high incentive condition with a higher response rate and thus were unable to achieve high levels of memory accuracy. The older adults demonstrated less effective monitoring ability, which the researchers stated was a result of a poorer ability to recollect details of events, and related to the participants' age.

Alternatively, the same population (students) can also vary in monitoring ability. Higham and Arnold (2007a) observed that students have varying levels of monitoring; specifically, higher achieving students monitor their knowledge best. Individuals who have good monitoring ability have a good chance of performing well on the test, assuming their control ability (knowing when to report an answer and when to withhold) is also good. However, this research implies that if a student takes the test with similar monitoring ability but ineffective control ability, s/he may report too many incorrect answers and withhold too many correct answers, and not perform as well.

Considered collectively, two broad theories appear to emerge from the metacognitive literature. One suggests that there are inconclusive and contradictory findings for explaining the exact interplay between monitoring and control aspects with regard to judgement and decision-making. Another thread is that while there is likely interdependence between monitoring and control, this association tends to vary in terms of breadth, depth and intensity, depending on a number of complex intrinsic and extrinsic variables.

Metacognition: Can it be Improved?

It is apparent that many factors, other than individuals' monitoring and control abilities, affect their regulation of accuracy (Zelazo, Moscovitch & Thompson, 2007). As these dimensions (e.g., goals, time pressure and incentives) are generally within the sphere of influence of decision-makers, it can be argued that knowledge/memory regulation can be improved somewhat through training. To cite one example, in educational contexts, practice tests have been shown to improve metacognitive performance (Chambres, Izaute & Marecaux, 2002). More specifically, King, Zechmeister and Shaughnessy (1980) found improved JOL predictions when participants were given five additional tests compared to additional study time. The participants in the additional test group increased their monitoring accuracy overall, even when different items were included in each test. Likewise, Rawson, Dunlosky and Thiede (2000) observed that simply re-reading a text before making JOLs improved metacognitive accuracy.

While these findings are positive, several studies have also demonstrated that once testing begins, individuals do not shift their response criteria, despite explicit instructions. In some studies, participants have been shown to be rigid with their criterion, regardless of extreme strength differences (strong and weak) associated with different categories of items at test (Morrell, Gaitan, & Wixted, 2002). The results of Higham and Arnold's (2007a) study suggest that feedback after a general knowledge test does not necessarily improve students' scores on a subsequent test. Participants completed three general knowledge tests and given feedback after each test as to their more optimal balance of "reported" (in which they would gain or lose points for correct and incorrect answers, respectively) and "guessed" (points won for a correct answer, no points deducted for an incorrect answer) responses. Students did not learn from their mistakes with this end-of-test feedback, and therefore did not shift their response criterion effectively enough. Similar findings were observed with trial-by-trial feedback in Higham (2007).

In contrast, other research supports the view that metacognitive processes, specifically control, can indeed be enhanced. With this end in mind, Han and Dobbins (2008) used a biased-feedback approach that subtly misinformed participants of commission and omission errors in order to get them to learn to favour one type of response or avoid another. Interestingly, the results demonstrated that the biased feedback yielded adaptive criterion shifts, signifying that the shifts are not necessarily under the participants' awareness or control. The researchers do, however, assert that this adaptive criterion shifting may be a different mechanism from criterion shifts that arise due to explicit instructions, or through manipulations of task demands that highlight the change in criterion, as in Morrell et al. (2002).

In another informative investigation, Batha and Carroll (2007) introduced metacognitive training to decision-making. Participants were divided into three decision-making abilities: average, below average, and above average. Participants in the experimental group received metacognitive strategy instructions, such as explicitly drawing participants' attention to the importance of correct strategy use and an explanation of how to use the strategies (which could relate to control processes) before taking part in a decision-making questionnaire. The results confirmed that the metacognitive training was beneficial only to the below-average group, and that the regulation of cognition had a greater impact on decision-making than did knowledge of cognition. Further, Rhodes and Jacoby (2007) examined whether participants could shift their criterion for recognition decisions in response to the probability that an item was previously studied. Three experiments confirmed that increased awareness and feedback on performance were key factors contributing to the criterion shifts.

Research highlights there are some contexts in which metacognitive processes are difficult to improve or alter. Most of the reviewed literature appears to demonstrate that feedback in training programs has a positive effect on where participants place their criterion. However, very little research has focused on whether monitoring can be improved by the training, and more research into this area has the potential to inform different populations of how better to strategically regulate their knowledge/memories.

Measuring Metacognition

Gamma correlations were once the main method used to measure monitoring resolution and confidence calibration bias (Nelson and Narens, 1994; Lichtenstein, Fischhoff, & Phillips, 1982). Over the past few decades, two influential frameworks have been developed to measure an individual's metacognitive processes: Type-2 Signal Detection Theory (SDT) and Koriat and Goldsmith's (1996) metacognitive framework.

SDT, a rational choice theory of decision-making under uncertainty, originated as a model of perceptual judgement (Tanner & Swets, 1954). Egan (1958) was one of the first researchers to apply SDT to recognition memory, as he realised that an old, studied item could be put into the equation as the signal, and a new, unstudied item could be put into the equation as the noise. This manipulation is known as a 'type-1' task in which an individual decides whether or not an event has occurred (Galvin, Podd, Drga & Whitmore, 2003; Macmillan & Creelman, 2005; Rotello, Macmillan & Reeder, 2004). In a classic recognition test it is assumed the participant's confidence relates to the degree of recognition, with greater confidence associated with old words and lower confidence associated with new words. At the time a type-1 decision is made, the individual has to decide whether the response is correct (*C*) or incorrect (*I*), and this discrimination is known as a 'type-2' decision. Type-2 decisions 'assess whether observers' confidence in the occurrence of the event matches the proportion of times that the event actually occurred' (Galvin et al., 2003, p. 845), and thus the discrepancy between the confidence and actual performance using type-2 SDT can indicate level of metacognitive ability. For instance, Higham (2002) demonstrated that report bias and monitoring ability could contaminate memory performance (retrieval).

The model on which this thesis focuses is a type-2 SDT Gaussian, equal-variance model that runs along a subjective dimension of confidence (see Figure 1.2). There are two distributions: the correct response and incorrect response distributions; better metacognitive monitoring is illustrated when the two distributions are farther apart. Higham (2002, 2007) has argued that type-2 discrimination constitutes a measure of *metacognitive monitoring* because it is based on an underlying confidence-accuracy relationship. The overlap between the two distributions indicates when the participants are unable to effectively discriminate between their correct and incorrect responses (i.e., when an incorrect response is reported (false alarm) or a correct response is withheld (miss)).

M*etacognitive control* is indicated by the report criterion in this model, which is set along the confidence dimension with reported answers associated with subjective higher confidences and withheld answers associated with subjective lower confidences. It is up to the individual how they set their response criterion. The report criterion in Figure 1.2 is currently unbiased. If the criterion shifts to the right, the figure would show a conservative report bias, and to the left, a liberal report bias.

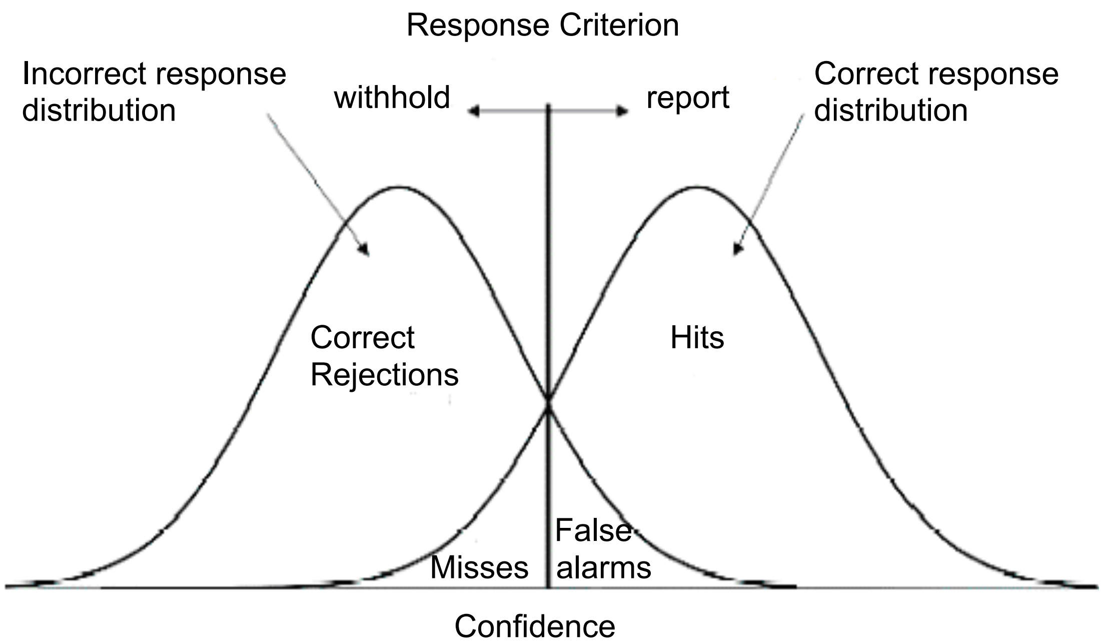

Figure 1.2. Equal-variance type-2 Signal Detection model (from Higham & Arnold, 2007a).

Shown in Table 1.1 is a 2 X 2 contingency table, which can be used to derive all the possible outcomes and measures to analyse performance. There are four possible contingencies shown in the table: a correct decision that is reported (hit [H]), an incorrect decision that is reported (false alarm [FA]), a correct decision that is withheld (miss [M]), and an incorrect decision that is withheld (correct rejection [CR]).

Table 1.1

The Four Task Contingencies Used to Derive all Measures of Performance.

	Decision	
Response	Correct	Incorrect
Report	Hits (Hs)	False Alarms (FAs)
Withhold	Misses (Ms)	Correct Rejections (CRs)

These four contingencies can be used to compute typical measures of performance such as total score, accuracy, and response bias (see Table 1.2), and they also allow for the computation of a type of hit rate (HR) and false alarm rate (FAR). The HR and FAR can be used to compute informative SDT performance measures that allow us to examine response control and how well individuals discriminate between their correct and incorrect decisions. Many of the measures listed in Table 1.2 will be used in the analyses of the following experiments.

Table 1.2

The Formulae for each Performance Measure that will be used Throughout the Following Experiments

Measures		Formulae
SDT	Hit Rate (HR)	Hs/(Hs+Ms)
	False Alarm Rate (FAR)	FAs/(FAs+CRs)
Outcome	Total Score	Hs*Reward – FAs*Penalty
	Overall Accuracy	(Hs+Ms)/(Hs+Ms+FAs+CRs)
	Gambling Accuracy	Hs/(Hs+FAs)
Monitoring	*d′*	z(HR) – z(FAR)
	Area Under ROC Curve (AUC)	$\frac{1}{2}\sum(y_{k+1}+y_k)(x_{k+1}-x_k)$[3] $\sum$ from $k = 0$ to n.
Bias	*C*	-0.5*(z[HR]+z[FAR])
	Gambling Likelihood	(Hs+FAs)/(Hs+Ms+FAs+CRs)

[3] y = cumulative HR; x = cumulative FAR; k = specific confidence level, n = highest confidence level.

Type-2 SDT has been employed to separate the underlying cognitive and metacognitive components of performance on a variety of tasks ranging including cued recall, educational testing and recognition. For example, Higham (2007) and Higham and Arnold (2007a) suggest that when formula scoring (that is, when incorrect answers are penalised to 'correct for guessing'; negative marking) is utilised in a testing situation, how students regulate their accuracy (i.e., which answers they decide to report) needs to be considered. Higham and Arnold propose that the negative marking format relies too heavily on an individual's metacognitive monitoring and control abilities, rather than a true representation of an individual's accuracy or knowledge and understanding. To illustrate, some students may be able to discriminate easily between what is correct and what is incorrect, and therefore avoid losing points. Alternatively, students who are poor at monitoring their own knowledge may offer incorrect responses when they believe them to be correct, or pass on correct responses, thus losing points as well as incurring the penalty. Higham and colleagues found in their experiments that although all the students tended to guess too often, resulting in less than optimal scores on multiple-choice tests, the students varied significantly in their ability to monitor their own knowledge. Type-2 SDT was useful in separating and measuring the various aspects of performance. The researchers were also able to demonstrate a link between student intellectual ability and accuracy of setting a response criterion and monitoring knowledge using this methodology.

Taking an alternate approach that builds on signal detection theory with concepts and method borrowed from the study of metacognition, Koriat and Goldsmith (1996) developed a 'QAP' (quantity-accuracy-performance) framework (see Figure 1.3) to measure both memory quantity and memory accuracy that is mediated by metacognitive processes. According to the framework, asking a question triggers a search in long-term memory that retrieves a candidate response and activates a monitoring process that assesses the correctness of the response. A "good" candidate response will be reported and a "bad" candidate response will be withheld, based on both the assessment of correctness and a pre-set response criterion that is centred on situational demands and payoffs.

The model is based on a two stage free-forced paradigm able to measure four parameters (Koriat & Goldsmith, 1996): 1) *overall retention* (retrieval of correct information); 2) *monitoring effectiveness* (the extent to which the subjective confidence judgements successfully differentiate between correct and incorrect responses); 3) *control sensitivity* (the extent to which the reporting or withholding of candidate answers is based on the monitoring output); and 4) *report criterion setting* (the report criterion above which answers are reported, and below which they are withheld. A number of studies have also provided support for this framework (Pansky, Goldsmith, Koriat & Pearlman-Avnion, 2008; Payne, Lambert & Jacoby, 2002; Rhodes & Kelley, 2005).

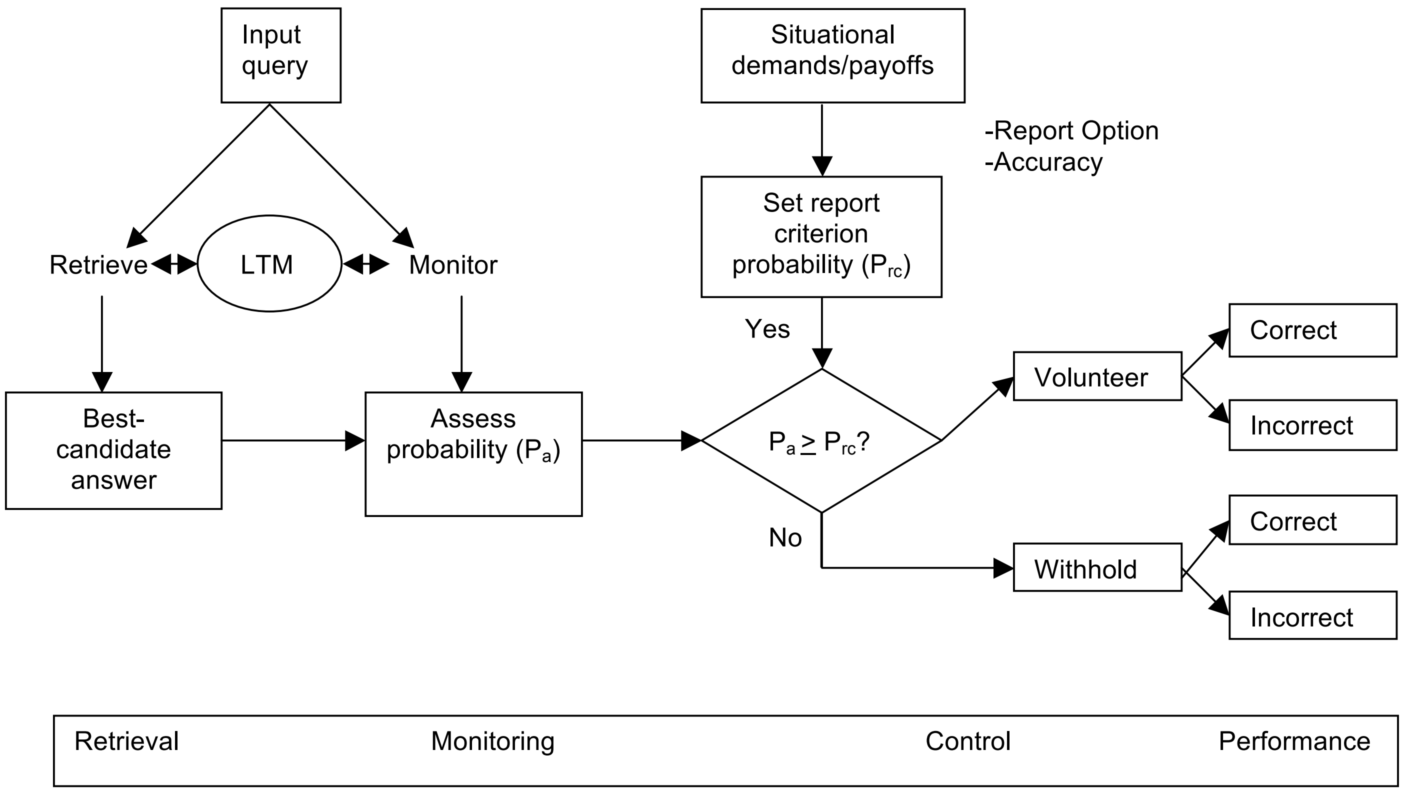

Figure 1.3. Koriat and Goldsmith's (1996) Framework displaying memory accuracy and memory quantity performance, with the control process of free-report. LTM = Long Term Memory.

Whilst the two approaches to measuring the cognitive and metacognitive components of memory share some similarities in the underlying psychological models, some of the performance measures and methods of analysis are distinctive. Koriat and Goldsmith (1996) have criticised SDT on the basis that they believe SDT does not separate memory strength from monitoring effectiveness. Then again, it can be argued that the researchers were referring to type-1 SDT (is a signal present?; yes/no paradigm) rather than the type-2 assessment of the correctness of one's response. In a type-2 context the report criterion helps to assess monitoring as individuals are assumed to 'report' high confidence responses, and 'guess' or 'withhold' low confidence responses. In addition, Goldsmith and Koriat (2008) suggest that their framework more directly assesses monitoring through confidence judgements. However, the confidence judgements are taken only during the forced-report stage, and Higham's (2002) countervailing view is that confidence judgements can change between free- and forced-report conditions. Goldsmith and Koriat (2008) further posit that they include a measure of control sensitivity that allows for them to measure the 'extent to which they [individuals] control their monitoring reporting on the basis of subjective confidence' (Goldsmith & Koriat, 2008, p. 28), and that this measure may be useful in examining how people vary their confidence reporting in different situations. Goldsmith and Koriat (2008) also argue that this measure of control sensitivity may increase understanding of memory accuracy in different populations, such as with older adults.

SDT generally assumes that high confidences will elicit reporting of responses, which has been confirmed in many educational and recognition studies (Goldsmith & Koriat, 2008, Higham, 2007). Receiver Operating Characteristics (ROCs) can be constructed from simple confidence ratings. ROC curves plot the hit rate (HR) against the false alarm (FAR) rate to indicate how well individuals can monitor their own knowledge; a deeper bow across the assigned confidences illustrates better discrimination. These give us an increased understanding of how individuals are discriminating between their responses in relation to different confidence levels, and can also be drawn for 'reported' and 'withheld' responses. The distance between the plotted confidence ratings is also indicative of the response bias, and gives an understanding of whether an individual is being very conservative or liberal, as well as how they are discriminating between the confidences (e.g., perhaps an individual is reporting all the decisions of which they are 4-6 on a confidence scale, but withholding all the decisions with very low confidence, such as 1-3 on the confidence scale). Thus, the ROC measure rivals control sensitivity (the degree to which the criterion is sensitive to output from a monitoring mechanisms) offered by Koriat and Goldsmith's framework.

Moreover, Higham and Arnold (2007a) have demonstrated that bias profiles can be constructed for each participant in order to further investigate how people are responding during a task (see Appendix A for the methodology to create bias profiles, and the computation of optimal bias). A bias profile is a plot of the corrected score (number of correct gambles – [incorrect gambles x penalty]) as a function of the proportion of 'withheld' responses. Bias profiles are based on individuals' tendency to make correct judgements and report correct answers using three distinct parameters: metacognitive monitoring (d'), accuracy (proportion of correct responses) and the penalty for errors. Optimal bias, that is, an individual's ideal criterion setting in order for him or her to gain the maximum number of points based on their level of knowledge and monitoring ability, can also be constructed (see Chapter 3 for a fuller description of bias profile and optimal bias; see also Higham, 2007a). The comparison between the actual and optimal performances (criterion setting) of individuals gives us a greater understanding of whether they are over- or underconfident, and whether this aids or impedes their decision-making.

SDT has been criticised on the grounds that some of the analysis measures to calculate performances can be sensitive to certain assumptions, for instance, using d' to measure discrimination has been shown to be sensitive to changes in bias (Evans & Azzopardi, 2007). However, Higham (2002) asserts that this is more of a problem when using d' or other parametric measures, than a criticism of SDT. Further, it is possible to compute and analyse FARs using SDT to determine whether bias measures have been affected by variation in other performance parameters, such as accuracy and/or monitoring (see Chapter 5). Finally, by utilising Receiver Operating Characteristic (ROC) curves, it is possible to calculate the area under the curve (AUC) which avoids the use of d'. AUC is a good index of discrimination, and it can be computed easily using the trapezoidal rule (Pollack & Hsieh, 1969). Computed in this way, AUC is a "truly nonparametric" (Macmillan & Creelman, 2005, p. 64) measure of discrimination, particularly if the nature of the underlying evidence distributions is unclear. AUC equals 1 if discrimination is perfect and 0.5 if it is at chance. This is true regardless of whether AUC is computed from a type-1 or type-2 ROC curve.

Notwithstanding some criticisms with the SDT framework, Goldsmith and Koriat (2008) maintain that SDT is a viable method for explicating differences in retrieval, monitoring and control processes in decisions of uncertainty.

Applying the Strategic Regulation of Accuracy to Gambling

Against these competing theoretical orientations, it may be questioned how the SDT approach can be used to assess the strategic regulation of accuracy in gambling. The game of 'blackjack' (which involves elements of both skill and chance) can be taken as an example. The basic concept of blackjack involves receiving the highest hand of playing cards without going over twenty-one; the player with the highest hand wins, and if a player's hand goes over twenty-one, they bust – or forfeit their hand. When players view their cards, they are able to (loosely) assess the probability of winning against the other players (monitoring). For instance, if the total of one player's cards is 19, then it would be assumed that he/she would utilise this knowledge by thinking that they have a good chance of winning the round and would act upon this information (control) accordingly. In this situation, it would be expected that a 'good' gambler would 'stand' on the value he/she already holds (rather than ask for another card in which there is only a very small probability that a '2' would be dealt). In contrast, a 'poor' gambler may try to risk their money and ask for another card to be dealt to add to their total.

Very few gambling research initiatives have focused on the strategic regulation of accuracy. Goodie (2005) examined how well bets were calibrated with individuals' answers across general knowledge questions. Participants were required to answer general knowledge questions, assess their confidence in each answer, and place a bet on that answer. If their bets were well calibrated with their answers, then they would win a fair amount back; if the bets were overconfident, the winnings were unfavourable. The findings confirmed that problem gamblers were more overconfident than non-problem (social) gamblers, and consequently earned significantly fewer points.

Further, the research that has utilised SDT to measure gambling performance has explored the role of consciousness in post-decision wagers, rather than determining differences between groups of gamblers. For instance, Persaud, McLeod and Cowey (2007) introduced an "objective measure of awareness" (p. 257) in which post-decision wagering was investigated in a gambling task. The participants took part in two tasks: an artificial grammar task, in which they were required to classify test strings of letters as grammatical, and an Iowa gambling task, which requires participants to select one of four positive yield and negative yield packs to eventually find the pack that produces a positive yield overall. Participants were required to wager large or small stakes on their correct decisions (and therefore discriminate between what they know and do not know). The findings demonstrated that participants performed above chance but failed to maximise their cash earnings by not gambling enough on their correct answers (being too conservative). Because the tasks measured both implicit (artificial grammar) and explicit (Iowa gambling task) learning, with participants performing similarly on each, Persaud et al. (2007) strongly argue that post-decision wagering is an intuitive measure. Also, because the findings support the assumption that individuals are not always conscious of their decisions (and fail to monitor their own knowledge), post-decision wagering is a direct measure of unconscious awareness.

Seth (2008) disputed Persaud and colleagues' (2007) claim that post-decision wagering measures performance without awareness. Seth put forward that post-decision wagering does not supply a direct measure of awareness, as this method cannot "exhaustively describe the rich phenomenology of conscious experience" (p. 982). He claims that only metacognitive content can be measured through post-decision wagering and argues that a variety of methods (including post-decision wagering, neurophysiological and theoretical frameworks) understand and measure consciousness. To some extent, Seth is correct in stating that post-decision wagering is only concerned with metacognitive content; however, if Persaud et al. (2007) used a theoretical framework, such as type-2 SDT, which distinguishes between the accuracy, monitoring and control parameters of performance, more conclusions may be drawn regarding how economics interacts with subjective confidence (see also Dienes & Seth, 2009).

Fleming and Dolan (2010) investigated how 'economic factors', such as different wager structures and loss aversion, affect decision-making (i.e., how the response bias shifts depending on the penalties). Specifically, participants became worse at discriminating between their correct and incorrect responses as the wagers increased in value. The authors state that these findings demonstrate that post-decision wagering is not an effective measure to illustrate an individual's lack of awareness, as there is a complex interaction between objective stimulus visibility, wager size, and willingness to gamble (related to loss aversion).

Discriminating between subjects' monitoring of correct decisions on the one hand and response strategy (how often one gambles vs. how often one passes) on the other, could be invaluable in distinguishing between different populations of gamblers, and further understanding the cognitive and metacognitive processes involved in decision-making. For instance, in terms of analysing decision-making using SDT, a gambler with good monitoring ability, or an individual who regularly gambles (practice), should correctly discriminate between advantageous and disadvantageous decisions, and therefore make fewer misses and false alarms than a poor gambler. It may also be hypothesised that 'good' gamblers are able to set a more appropriate gambling criterion as they would be more aware of a more complete picture of the situation and act accordingly. Also, from Goodie's (2005) research, it could be inferred that PGs will exhibit overconfidence in their gambling behaviour on gambling tasks. These individuals may find it difficult to monitor their chances of winning, and may also struggle to identify when it is suitable to gamble and when to guess. Establishing cognitive distinctions between subgroups of gamblers using an SDT framework may have significant implications for interventions and treatment programmes.

Research Questions

The present research described in this thesis will be the first to explore the decision-making of different groups of gamblers and non-gamblers using SDT. Rather than focusing on the controversies involved with measuring conscious awareness, the research aims to provide insight into the metacognitive differences between non-gamblers, regular non-problem gamblers, and problem gamblers, which may in turn contribute to our understanding of why some individuals develop gambling problems, whilst others do not. More specifically, the fundamental research questions that the thesis was designed to explore are:

- *Are there substantial cognitive and metacognitive differences between problem, non-problem and non-gamblers, and if so, what are these components?*
- *Does previous experience with gambling impact on cognitive and metacognitive variation?*
- *Can individuals be trained to improve resolution, gambling criterion and accuracy? If so, could feedback and training impact on potential treatment interventions?*

- *To what extent does Type-2 Signal Detection Theory inform our understanding of gambling behaviour and contribute to the literature on gambling?*

Summary

To date, the cognitive gambling research has been dominated by the investigation of cognitive distortions and irrational beliefs between problem and non-problem gamblers. Whilst there is a general consensus that problem gamblers hold more irrational beliefs than non-problem gamblers, there is some inconsistency in the research and a difficulty in differentiating cause and effect. Moreover, evidence suggests that examining variations or differences between sub-types of gamblers would contribute to our understanding of gambling behaviour.

Metacognitive research in the fields of memory and education has demonstrated that individuals can strategically regulate accuracy; however, metacognitive processes of monitoring and control can be affected by many different factors, such as task demands and accuracy-quantity tradeoffs. Importantly, this literature has been inconsistent in determining the interplay between monitoring and control. Signal Detection Theory has been criticised for relying too heavily on certain assumptions, but this framework has been shown to be effective in separating the cognitive and metacognitive components of memory, and is potentially more incisive than Koriat and Goldsmith's QAP methodology, particularly with the use of bias profiles for plotting actual versus optimal response criteria.

Metacognition, a major focus of research interest in cognitive psychology, is a fundamental dimension of everyday remembering and learning. As an emerging complex psychological phenomenon, it holds the potential for applications in diverse contexts, investigating 'knowledge under uncertainty', such as gambling.

The six chapters that follow aim to expand our understanding of the current cognitive literature through original experiments that examine variation among different gambling populations. In addition, the chapters will add to the literature through the application and discussion of an innovative quantitative research methodology that previously has had very little consideration in the gambling domain.

CHAPTER 2
METACOGNITIVE PROCESSES, EXPERIENCE AND GAMBLING BEHAVIOUR: OPTIMISING TASK SUITABILITY

Why do some people develop gambling problems while most don't? There have been many explanations for gambling compulsion or dependence, ranging from social learning theory to the neuropsychological. (e.g., Diskin & Hodgins, 2003; Hardoon, Baboushkin, Derevensky & Gupta, 2001; Langer, 1975; Rachlin, 1990; Raylu & Oei, 2002; Studer & Clark, 2011). Theorist justifications for problem gambling vary widely, but there is general consensus that it is the loss of control or high-risk impulsivity of gambling behaviour that can transform 'normal' human behaviour into, what may seem to many, 'irrational' or illogical behaviour.

Coventry (2008) observes that this loss of control 'presents a considerable challenge for general theories of addiction' (p. 444). Unlike substance and alcohol abuse, that has both physiological and psychological effects on the brain, problem gambling does not involve the intake of substances. Problem gambling, essentially an impulse control disorder, is an urge to continuously gamble despite potentially harmful or negative consequences, but shares similarity of characteristics to other addictions, in terms of tolerance, withdrawal symptoms and lack of self-control (Dickerson & Baron, 2000; Petry, 2006). Further, it is argued that the majority of the Western population gambles to some degree, but fortunately, it is only a small percentage that develops problematic and pathological gambling tendencies.

As highlighted in Chapter 1, cognitive gambling research has established that problem gamblers hold many more cognitive distortions or biases than non-problem gamblers in relation to the probability of winning money when faced with uncontrollable and chance events. Whilst we can examine the link between erroneous beliefs and irrational gambling behaviours, there is little evidence to imply that cognitive biases directly link to the development of problem gambling behaviour, especially given the second point highlighted above. Cognitive biases and irrational beliefs are evident in both problem gamblers and non-problem gamblers (Delfabbro, 2004; Ladouceur, 2004; Ladouceur & Walker, 1996; Horton, Turner & Fritz, 2006), so it may be that other variables are interacting with or are impacting on an individual's irrational beliefs, which could lead to problematic gambling.

Several hypotheses have been proposed to account for the crucial link from gamblers' maladaptive thinking to problem gambling. Griffiths (1999) suggested that structural characteristics of electronic gaming machines (EGMs), such as the speed of play, frequent wins, 'near misses', lights, and sounds, contribute to their addictive properties (see also Breen, 2004; Breen & Zimmerman, 2002; Loba, Stewart, Klein & Blackburn, 2002; Morgan, Kofoed, Buchkoski & Carr, 1996; Turner & Horbay, 2004). Conversely, Lambos and Delfabbro (2007) assessed problem gamblers and non-gamblers numerical reasoning skills, objective gambling knowledge, and tendency towards biased reasoning. The problem gamblers demonstrated a significantly greater number of cognitive biases; however, this difference could not be attributed to poorer knowledge of gambling odds or poorer numerical reasoning skills (see also Parke et al., 2005; Turner, et al., 2006).

Consequently, the relationship between cognitive biases and problematic gambling behaviour remains very ambiguous. On the other hand, the inconsistency of the irrational gambling literature could be partially explained by the methods employed to investigate differences between groups. Traditionally, one of the main procedures used to research irrational beliefs is the "thinking aloud" approach, which consists of participants verbalising every thought or idea whilst performing a gambling task, with verbalisations being recorded for transcription and qualitative analysis (Gaboury & Ladouceur, 1989; Griffiths, 1994, 1996; Toneatto, 1999). Other methods to clarify cognitive differences between gambling groups have included questionnaire and self-report methods (Toneatto, Blitz-Miller, Calderwood, Dragonetti & Tsanos, 1997; Joukhador, Blaszczynski & MacCallum, 2004). Although the self-report methods are insightful in exploring in-depth the types of cognitive biases and heuristics that individuals experience when gambling, and raising the ecological validity of gambling research, these approaches are also limiting due to three main assumptions. They assume that: 1) participants are giving a full description of their thought processes, judgements, and cognitions during the verbalisations when in fact they may be holding back or offering additional information which they may not necessarily believe; 2) the verbal protocols are not interfering with their gambling behaviour; and, 3) perhaps most importantly, such processes are consciously available and under the individuals' intentional control (McCusker & Gettings, 1997). Appropriately, researchers have started to move towards more objective methods to measure and understand cognitive biases to compliment the more subjective verbal protocols.

An alternative view that may contribute to the irrational belief literature is the notion that some gamblers may switch to an automatic pilot mode that leads them to continue gambling irrationally and make poor decisions, despite facing substantial losses. McCusker and Gettings (1997) examined the automaticity of cognitive biases. The researchers compared compulsive gamblers with a non-gambling control group on a modified Stroop task (that involved participants engaging in a timed task of colour-naming the ink in which a series of words are printed) and an implicit word-stem completion task, of which many of the words were primed during the Stroop task. McCusker and Gettings found that the compulsive gamblers were slower on the Stroop task for gambling-related words than for neutral and drug-related words, and the compulsive gamblers also completed more of the gambling-related word-stem words. The researchers proposed that this is evidence for an automatic processing bias, rather than explained by the emotional saliency of the words (as drug-related words were also incorporated into the experiments), which makes the intentional suppression of gambling-related information difficult. The work builds on Griffiths' (1994) study which reported that pathological gamblers 'could not believe what they had said and how they were thinking while gambling' (p. 367), after the gamblers heard a playback of their irrational verbalisations. Griffiths suggested that the gamblers' 'thinking aloud' was outside of conscious awareness. An alternative standpoint is that the gamblers either forgot the content of what they had verbalised, or they failed to pay attention to their verbalisations as they were distracted with the gambling task.

Considering the distinction between conscious and unconscious awareness of behaviour in relation to cognitive biases may give us further insight into why some gamblers continue to gamble problematically. Lambos and Delfabbro (2007) have projected that further research in understanding the conscious/unconscious cognitive biases that both problem and non-problem gamblers experience is crucial in order for the research to contribute to future treatment programmes.

A Dual Process Account of Gambling

In recent years, a different approach to understanding the irrational beliefs of individuals has emerged, known as cognitive dual process theory (Amsel, Close, Sadler & Klaczynski, 2009; Epstein & Pacini, 1999; Evans & Coventry, 2006; Hammond, 1996; Toplak, Liu, Macpherson, Toneatto & Stanovich, 2007). There are many different interpretations of the theory with each theorist contributing to our understanding of a two systems account of reasoning, but there are many commonalities and overlaps among the theories (Osman, 2004). Generally, dual process theory proposes that there are two biologically distinct cognitive systems which underlie thought processing, reasoning and decision-making: an implicit, experiential system, that Kahneman (2003) termed 'intuition', is evolutionary older and is thought to be similar to the cognitive systems of higher animals. It is rapid, emotional, associative and heuristic-based, and only the final outcomes of the automatic and 'unconscious' processing of learned experiences reach conscious awareness (Epstein, 1994; Evans & Coventry, 2006; termed 'System 1' in Stanovich & West, 2000). Experiential processing generally relies on knowledge and content from experiences, which can be effective in some circumstances, but not others.

The other intellectual processing system (labelled 'reasoning' by Kahneman, 2003) is an explicit, analytical system ('System 2' in Stanovich & West, 2000), which is much slower, systematic and sequential, and associated with abstract thought. This system is unique to humans and largely within conscious awareness and requires knowledge and skills that are acquired in specific contexts. Being cognitively effortful, it is argued that this system can override the experiential system, often resulting in more logical and rational responses. The two systems run parallel to each other, but interact simultaneously in decision-making contexts, depending on an individual's skill, knowledge and experience (Sloman, 2002). The difficulty faced by most people is that the experiential system may be very useful in some circumstances, but the heuristics may be applied erroneously to other situations, which leads the individual to make non-beneficial and costly decisions (Klaczynski, 2000; Wagenaar, 1988); a 'rational thinking failure'? (De Neys, 2006, p. 428).

Researchers have suggested that these regulations may contribute to gambling addiction. Evans and Coventry (2006) emphasised, in relation to gambling, that individuals misapply heuristics that usually work for them, in situations where general principles should not be applied. For instance, real-world environments are 'noisy' with varying amounts of additional and unnecessary information, and humans have evolved to detect complex patterns in the environment implicitly, without the need for the use of the more effortful analytic system. The difficulty with some gambling games (i.e., chance games such as roulette) is that they have been designed to be completely random with no sequential dependency between outcomes. Most of the gambling activities played regularly involve chance outcomes (e.g., roulette, slot machines, lotteries), or very little skill (e.g., blackjack). This lack of sequence between events poses a problem for the analytical system that automatically draws together meaning and reasoning from randomness: it is not a rational act to gamble lots of money on a game that has a negative expected return. The experiential system is programmed to learn patterns, but in the case of gambling this is an inappropriate reaction. Evidence for gamblers to find a pattern in independent events can be observed in their reliance on past outcomes in predicting future outcomes (e.g., Coventry, 2002; Langer & Roth, 1975). For example, Ladouceur and Dubé (1997) explored gambling predictions of undergraduate students on a simple heads or tails coin toss. The majority of students paid a proportion of their study payment to view the previous outcomes (an option offered by the experimenters), despite the researchers making the students aware of equal chances of the coin landing on heads or tails.

Moreover, Coventry and Norman (1998) have suggested that irrational beliefs may be a consequence of the gambling behaviour, rather than the cause. The researchers argued that if gambling behaviour is actually being controlled by the experiential system, then the analytic system tries to 'make sense' of the behaviour and develops beliefs that make it appear more rational, such as attending to wins more often than loses (Rachlin, 2000). However, despite the sparse evidence for this assumption, the pertinent question still remains: 'why is it that only a small proportion of individuals fail to control their gambling?'

It has been suggested that metacognition facilitates the regulation between the two systems (Amsel, Klaczynski, Johnston, Bench, Close, Sadler & Walker, 2008; Kirkpatrick & Epstein, 1992; Klaczynski, 2004, 2005). In essence, someone who can monitor both systems knows when the analytical system is needed to override the experiential system; when the higher-order brain needs to inform the player of when to walk away. Kirkpatrick and Epstein (1992) examined the dual-process model in students' gambling decision-making. The researchers asked students to play a lottery with two trays: one tray had a 10:100 chance of winning, whilst the other tray had a 1:10 chance of winning. Participants tended to choose the tray with more winning tickets (10:100), despite the odds of the two trays being exactly the same. The researchers termed the tendency to prefer one of two equal gambles the ratio-bias effect, and posited that this bias was strongest in conditions that minimise the analytic processing of gambling information.

Amsel, Close, Sadler & Klaczynski (2009) explored students' awareness of their irrational judgements on decision tasks. Participants rated the certainty of ratio-bias decisions as being rational or irrational (as in Kirkpatrick and Epstein, 1992), above, in either a gambling or employment context. The researchers presupposed that the rational and irrational decisions reflect analytically-based and experientially-based processing, respectively. Individuals with poorer metacognitive status, that is, students who were unaware of their analytical processing and made decisions that were biased towards one of the two equal ratios, gambled more irrationally than those with a competent metacognitive status. Individuals with a competent status were significantly less biased in processing the ratio information. Amsel et al. (2009) interpreted the findings as demonstrating that how students regulate their dual processes (awareness of their analytic and experiential processes) can determine a vulnerability to irrational gambling and decision-making behaviour. The researchers hypothesised that this may also be the case in problem gamblers, with problem gamblers potentially having poorer metacognitive status, and, therefore more vulnerable to irrational gambling beliefs and behaviours.

Research has examined both the relationship of higher order 'mindware' problems with problem gambling (Toplak, Liu, Macpherson, Toneatto and Stanovich, 2007), that is, the knowledge and procedural gaps for dealing with probabilistic events, and inhibitory control on reasoning tasks (Kwon, Lawson, Chung & Kim, 2000). However, considerably more research investigating the metacognitive ability (both monitoring and control, as acknowledged in Chapter 1) of different subgroups of gamblers is clearly necessary before we can draw more substantial conclusions between irrational beliefs, metacognitive ability and gambling behaviour. Moreover, acknowledging that metacognition is not just one concept, but incorporates both monitoring and control, which may or may not interact in different circumstances, is also fundamental in any research on the self-regulation of behaviour. Establishing whether it is one or both processes, or an interaction of the two that is exerted differently in problem gamblers compared to non-problem gamblers, may further contribute to the irrational belief literature and our understanding of why some individuals fall into gambling problematically.

In this chapter, I focus on the development of a task that allows us to explore gambling behaviour using type-2 Signal Detection Theory. It is by the application of this model that we may be able to gain a deeper understanding of the self-regulation of individuals in gambling contexts, thereby beginning to address some of the issues and relationships raised in this introduction. Specifically, the model can objectively discriminate between two central metacognitive processes: monitoring and control. In Experiment 1, the SDT framework is applied to a simplified game of Blackjack.

Experiment 1
Penalty Manipulation in a Simplified Blackjack Task

Much empirical research has provided evidence for a lack of self-regulation when it comes to making decisions, such as inaccurate confidence-accuracy relationships and non-optimal subjective probability judgements (Lichtenstein & Fischhoff, 1977; Fischhoff, Slovic & Lichtenstein, 1977; Braun & Yaniv, 1992; Lindsay & Norman, 1972). Specifically, poor calibration between individuals' subjective and objective probability estimates has been demonstrated in difficult and easy to discriminate circumstances leading to overconfidence and underconfidence, respectively (the *hard-easy* effect, Suantek, Bolger, & Ferrell, 1996; Lichtenstein, Fischhoff, & Phillips, 1977). Various explanations have been proposed for miscalibration effects, including cognitive biases (Griffin & Tversky, 1992), various aspects of the decision environment, such as the role of random error (Erev, Wallsten & Budescu, 1994).

It has been suggested that by observing individuals who are experienced in a task, the level of miscalibration may be reduced, although there have been mixed findings. On the one hand, many studies have concluded that experienced individuals still make highly biased and/or overconfident decisions and poorly calibrated probability judgements (Wagenaar & Keren, 1985; Lin & Bier, 2008). On the other hand, it has been demonstrated that experienced individuals, or individuals who have been trained on a certain task make fewer errors and are better calibrated than naïve individuals (e.g., Peterson & Beach, 1967). For instance, Getty, Pickett, D'Orsi and Swets (1988) developed a training program for apprentice radiologists to distinguish between normal and abnormal x-rays, resulting in the trained radiologists being significantly more sensitive in their discriminating capacity after training.

Unsurprisingly, in most cases, 'expert' decision-making surpasses 'amateur' judgements, but research on the transference of expert performance to novel situations appears to hold some conflicting perspectives (Schwartz, Bransford, & Sears, 2005).

Some research has suggested that when experts are taken out of their area of specialism, their expertise diminishes or weakens. For instance, de Groot (1965) studied chess experts and their superior memory for chess positions. When the experts were presented with a random placement of pieces, rather than plausible game positions, the experts' superiority disappeared, and they had memory similar to novices. Conversely, other research has proposed that experts approach problem solving differently to amateurs. Gauthier, Williams, Tarr and Tanaka (1998) trained individuals on artificial object recognition (i.e., Greebles), and the findings demonstrated that the 'experts' could learn names of newly encountered Greebles at a quicker rate than novices. Most important to the present investigation, whilst research on the irrational beliefs of problem gamblers has been insightful, few pieces of research have given us substantial empirical research of the metacognitive processes, which may play a significant role in understanding the development of problem gambling. Further, little is known about the dynamics of more experienced gamblers, and whether they differ significantly in their decision-making to novice players.

A working hypothesis of the present study is that experienced gamblers may develop expertise[4] in accurately assessing when to bet and when to walk away (control), and better knowledge of their correct and incorrect decisions (resolution). Therefore, as long as regular gambling does not result in problem gambling, regular gamblers should perform better than non-gamblers on these two performance parameters, when given a skill-based task similar to what is available to play in gaming venues. In this way, gambling expertise develops in much the same way as other forms of expertise development, as long as the games that are practiced are not purely based on chance (e.g., lottery tickets), similarly to professional poker players. Alternatively, because gambling has a chance element, even in games of blackjack and poker that are considered skill-based games, it may be difficult for individuals who gamble regularly to develop gambling expertise. Given this idea, we would expect regular gamblers to perform similarly to non-gamblers.

[4] The expertise hypothesis originated from an early version of the published paper (Chapter 4), written by Dr P. Higham and me.

Research into how metacognitive monitoring and gambling control vary in individuals who have not gambled previously and in individuals who gamble regularly but show no signs of problematic behaviour is important because it may provide us with further insights into the development of problem gambling.

The Development of a Gambling Task Using Type-2 SDT

In order to determine the extent to which metacognitive ability plays a role in problem gambling behaviour, a task that allows the measurement of both the gambling criterion (metacognitive control) and resolution (metacognitive monitoring) needed to be created. The aim of this study was to develop a task that is both ecologically valid and allows the researcher to separate the monitoring and control processes of metacognition.

Table 2.1

The Four Task Contingencies Used to Derive all Measures of Gambling Performance.

	Decision	
Gambling Response	Correct	Incorrect
Gamble	Hits (Hs)	False Alarms (FAs)
Guess	Misses (Ms)	Correct Rejections (CRs)

It was decided that a gambling task that would allow decisions to be classified into one of the four contingencies of Table 1.1 was required, to enable the objective measurement of several performance components, including gambling control and metacognitive monitoring. As can be seen in Table 2.1, the ‘report’ and ‘withhold’ protocol can be modified for a gambling decision by changing the response criterion to ‘gamble’ and ‘guess’ (essentially passing the trial). This guess option allows us to view the decision that individuals *would have* made, even if they were not confident enough to place money or points on the decision. The guess decision also helps to ascertain whether participants are monitoring the correctness of their decisions appropriately or not. All four possible contingencies remain the same as in Table 1.1, but a H represents a correct decision that has been gambled, a FA is an incorrect decision that has been gambled, a M is a correct decision that is guessed, and a CR is an incorrect decision that is guessed.

Study Overview

The aim of the study was twofold. The primary aim of the experiment is to extend the type-2 SDT framework to the gambling domain. A second aim of the study was to potentially uncover differences in the underlying cognitive and metacognitive components of RGs and NGs. A simplified blackjack task was chosen to determine its suitability for exploring differences between these groups of individuals. If successful, problem gamblers were to be tested in future studies (see Experiment 6, Chapter 5).

As outlined in detail in Chapter 1, the application of SDT allows us to separate the contributions of discrimination (metacognitive monitoring), gambling bias, and accuracy on gambling performance. On the one hand, if regular gambling experience produces expertise, it might be expected that the regular gamblers (RGs) will be more sensitive to bias manipulations and set more optimal gambling criteria than the non-gamblers (NGs). On the other hand, as the gamblers recruited for this experiment played a range of gambling activities monthly, we might anticipate that general gambling experience does not result in expertise in gambling outcomes and betting control on a specific task. In Experiment 1, bias was manipulated by varying task penalty for errors (FAs).

Method

Participants

Twenty-nine regular gamblers (non-problem) and 29 non-gamblers aged between 18 and 38 years (M = 21.83; SD = 4.63) participated in Experiments 1 and 2 (see Chapter 3 for Experiment 2). A total of 25 females and 33 males (staff, and current or previous students) volunteered to participate after reading an advertisement on the University of Southampton's campus. Regular gamblers (RGs) were classified as individuals who gambled at least once a month on any gambling activities that involved money, such as going to casinos, betting shops, bingo, gaming venues or playing online or with friends. Participants who scored 3 or above on the *South Oaks Gambling Screen* (SOGS; see Lesieur & Blume, 1993) were excluded from the study as they were potentially problematic gamblers, and non-problem gamblers were the main focus.

The majority of participants completed the experiment in a research laboratory on campus, but the blackjack task was also sent to 30 percent of the participants by email to gain access to a greater number of participants. There were no differences in the results between the data completed in the lab and the data completed at the participants' own convenience. Participants were offered £6 as an incentive for completing Experiments 1 and 2 (counterbalanced to avoid order effects). Additionally, an incentive of £20 worth of vouchers was offered to the highest scoring individual to encourage more realistic gambling behaviour.

Design and Materials

Participants completed the *Hospital Anxiety and Depression Scale (HADS,* Zigmond & Snaith, 1983; see Appendix B) questionnaire containing 14 items (seven items on depression [HADS-D] and seven items on anxiety [HADS-A]). Each item is scored from 0 (minimally present) to 3 (maximally present), giving maximum scores of 21 for each subscale. A score of 11 or more on a subscale is considered to be diagnostic of either an anxiety or depressive disorder. Scores of 8-10 represents 'borderline' problems and scores of 0-7 are within the 'normal' range.

The *South Oaks Gambling Screen – Revised (SOGS,* Lesieur & Blume, 1993; see Appendix C) was also administered to participants. The SOGS is a 16-item psychometrically validated measure of pathological gambling. Items reflect symptoms of pathological gambling. A criterion score of 5 or more has been validated for identifying pathological gamblers, and a score of 3 or 4 represents an individual who may have some gambling issues. Therefore, participants who gambled regularly (at least once a month) and scored less than 3 on the SOGS were included in the study. Although the SOGS has been primarily employed as a screening device to identify problem gamblers, the present study uses the SOGS as an index of gambling severity. Many studies have suggested that whilst most screening instruments have limitations, the SOGS is an appropriate measure in discriminating non-problem gamblers from problematic gamblers (Oliveira, Silva, da Silveira, 2002; Weinstock, Whelan, Meyers & McCausland, 2007).

Blackjack Task. A computerised gambling task, a simplified version of blackjack, was programmed on an Apple Mac computer using the software 'Revolution'. In this game, participants were presented with two playing cards and shown one of two playing cards from the 'dealer'. The objective of the game was to make the most *advantageous* decision without going over 21. Ten thousand blackjack simulations were run, in order to calculate approximate chances of winning (primarily advantageous and disadvantageous gambles), given certain cards dealt to the player and the dealer. Generally, these simulations corresponded with 'basic strategy' tables of blackjack, for example, with a basic rule to 'hold' if the dealt cards equalled 17 or more. Aces were valued at both 1 and 11, as in the actual game of blackjack. Extra features of the games such as the opportunity to 'split' (splitting a two-card hand into two to play them separately) and placing an 'insurance' side bet (betting up to half the initial bet against the dealer having a natural 21) were removed from the game as it was necessary to have strict control over the underlying probabilities in order to work out what would be the most advantageous decision based on the cards, and be able to apply the data to signal detection theory. Cards presented to the participants were randomised with replacement from a virtual deck.

The gambling decision that was the main focus of the study was whether participants believed the decision to 'hit' (ask for another card to be dealt) or 'hold' (stick with the cards they have) would be most advantageous. Participants selected the 'hit' or 'hold' decision and were then required to make a confidence judgement based on that decision, which corresponded to how confident they were in the correctness of that decision. Finally, participants were required to indicate if they wanted to 'gamble' (in which they would gain or lose points for a correct or incorrect decision, respectively) or 'guess' (in which no points would be gained or lost for correct or incorrect decisions) on their hit/hold decision. To simplify the game, participants only played the first round of blackjack using their two cards shown and so would not progress onto the next stage of the game after they made a 'hit' or 'hold' decision.

The penalty for FAs was manipulated across two conditions of the blackjack task. In both conditions, participants would gain 1 point for a H. The 'low' and 'high' penalty conditions consisted of participants losing 1 and 4 points for FAs, respectively. No points were assigned to either CRs or Ms.

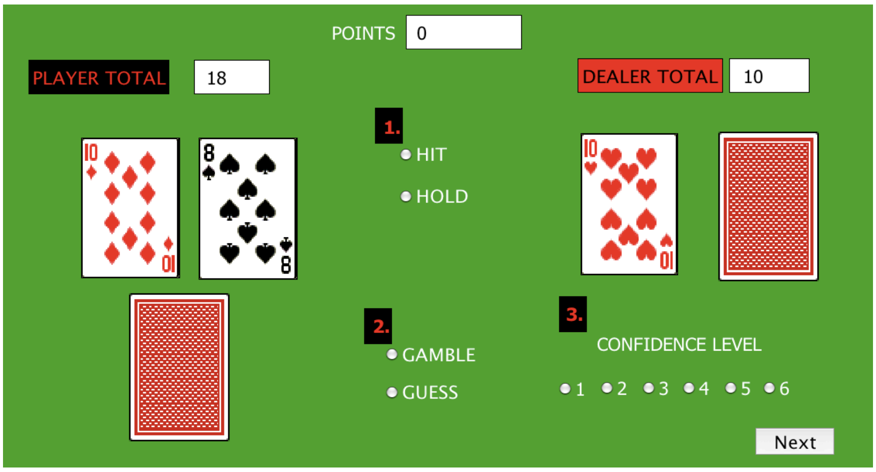

Figure 2.1. The blackjack task trial layout.

Procedure

The research protocol was reviewed and approved by the University of Southampton's Psychology Ethics. Initially, the SOGS was emailed to all volunteers to determine their eligibility to participate. Individuals who qualified for the study (i.e., gambled on a regular basis without indicating any problem gambling behaviours, or did not gamble at all) were then given (or sent if participating over email) an informed-consent form, along with demographic questionnaires and the HADS.

The computer-based task was administered in a counter-balanced order with half of the participants in each group participating in the low-penalty condition followed by the high-penalty condition, and the other half participating in the conditions in the reverse order. Seventy-two card trials were randomly selected from the simulation for each condition, and then presented in a single random order to all participants. Participants were tested individually and full instructions on how to run the program, the rules of the game, and what to do after completion of the task were given in writing. Participants were initially required to complete 5 practice trials to become accustomed to the task. After this presentation, participants were required to make three selections on the same screen (as outlined in the task description, above). Once the first condition was completed, participants had a two-minute break and then began the trials for the alternative condition (another 72 trials). The trials were self-paced and an additional break of two minutes was incorporated mid-way through each set of trials (three breaks in total).

Participants were given immediate feedback on their responses in the form of a 'points' box in the top right of the computer screen accompanied by either a 'ding' or 'buzzer' sound through headphones to indicate a correct or incorrect answer, respectively. Participants who took part at home were instructed to situate themselves in a quiet room with no people or audio distractions, and to increase sound on their computer so they could clearly hear the audio feedback. An incentive of £20 worth of vouchers was also offered to the individual who scored the highest number of points across both tasks, in order to encourage more realistic gambling behaviour.

A debriefing statement revealing the main hypotheses of the experiment followed the gambling task. Information on where to seek help with gambling problems, if needed, was also supplied (although no participants were PGs).

Results

Total Scores and Accuracy

A 2 (condition: high-penalty, low-penalty) X 2 (group: NGs, RGs) mixed ANOVA was conducted with group as the between-participants variable and condition as the within-participants variable (see Table 2.2 for the mean scores per condition). The ANOVA yielded a significant main effect of condition, $F(1, 56) = 30.07$, $MSE = 534.18$, $\eta_p^2 = .35$, $p < .001$. Participants completed the blackjack task with a higher score in the low-penalty condition ($M = 46.29$, $SEM = 2.16$) compared to the high-penalty condition ($M = 22.76$, $SEM = 4.93$), as expected. The main effect of group and the group by condition interaction were not significant, largest $F(1, 56) = 2.17$, $p = .15$.

Accuracy was defined as the most advantageous decision, which was selecting 'hit' to cards totalling less than 17 and 'hold' to a hand of cards that equalled or exceeded 17. Accuracy across all trials was computed for each participant (see Table 1.2 for the computation of overall accuracy using the four contingency frequencies, and Table 2.2 for the accuracy means). A 2 (condition: high-penalty, low-penalty) X 2 (group: NGs, RGs) mixed ANOVA was conducted on the data, with group as the between-participants variable and condition as the within-participants variable. The analysis found no difference in accuracy between the RGs and NGs, and no other main effects or interactions, all $Fs < 1$. Accuracy was not expected to differ between the two conditions as the same set of sums was presented in both the low-penalty and high-penalty conditions.

Table 2.2

Mean Total Scores and Overall Accuracy for Regular Gamblers and Non-gamblers in the Two Penalty Conditions of Experiment 1.

Group	Measure	
	Total Score	Accuracy
	Low-Penalty Condition	
NG	43.48 (3.05)	.87 (.02)
RG	49.10 (3.05)	.86 (.02)
	High-Penalty Condition	
NG	26.28 (7.00)	.87 (.02)
RG	19.24 (7.00)	.86 (.02)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Resolution

How well the RGs and NGs discriminated between their correct and incorrect decisions (resolution) was measured by *d′* ("d-prime", see Higham, 2007, or Galvin et al., 2003). *d′* is the difference between the z-transforms of the HR and FAR (see Table 1.2 for the calculation of *d′*). Greater *d′* indicates greater ability to discriminate between correct versus incorrect decisions, with zero representing chance performance. Some participants (5 NGs and 9 RGs) only 'gambled' across all trials in the low-penalty condition, which resulted in undefined HRs and FARs. Therefore, 0.5 was added to all frequency cells prior to the *d′* and *c* (gambling criterion, see below) analyses to avoid extreme HR and FAR proportions (Fleming & Dolan, 2010; Hautus, 1995; Macmillan & Creelman, 2005; Snodgrass & Corwin, 1988; see Table 2.3 for the means and SEs). For example, in calculating the HR of an individual with 30 Hs and 0 Ms (actual HR = 1), 0.5 would be added to each cell frequency and the number would be divided by n + 1; therefore, the adjusted HR would be 30.5/31 = .98.

A 2 (condition: high-penalty, low-penalty) X 2 (group: NGs, RGs) mixed ANOVA on *d′*, with repeated measures only on the former factor, revealed a main effect of group, $F(1,56) = 5.17$, $MSE = .75$, $\eta_p^2 = .08$, $p = .03$. The RGs ($M = 1.00$, $SEM = .11$) had better resolution than the NGs ($M = .63$, $SEM = .11$). The main effect of condition and the condition by group interaction were not significant, largest $F(1, 56) = 1.87$, $p = .18$.

Gambling Criterion

A 2 (condition: high-penalty, low penalty) X 2 (group: NGs, RGs) mixed ANOVA on *c*, with repeated measures only on the former, was conducted to determine whether the participants were setting a biased criterion (see Table 2.3 for the means). Positive values of *c* indicate conservative responding (i.e., when individuals decide to withhold their decisions, by selecting the 'guess' option), negative values represent liberal responding (i.e., when individuals select the 'gamble' option and report their decisions), and 0 indicates a neutral criterion. The ANOVA revealed a main effect of condition, $F(1,56) = 23.30$, $MSE = .19$, $\eta_p^2 = .29$, $p < .001$. Participants set a much more liberal criterion in the low-penalty condition ($M = -1.01$, $SEM = .11$) compared to the high-penalty condition ($M = -.63$, $SEM = .12$), as expected. The main effect of group and the group by condition interaction were not significant, largest $F(1,56) = 2.39$, $p = .13$.

Table 2.3

Mean Resolution, Bias, and Confidence Ratings for Regular Gamblers and Non-gamblers in the Two Penalty Conditions of Experiment 1.

	Performance Measure		
Group	Resolution (*d'*)	Gambling Criterion (*c*)	Confidence Rating (1-6)
		Low-Penalty Condition	
NG	.48 (.12)	-.85 (.15)	3.77 (.14)
RG	.99 (.12)	-1.18 (.15)	3.81 (.14)
		High-Penalty Condition	
NG	.78 (.16)	-.46 (.17)	3.77 (.15)
RG	1.01 (.16)	-.79 (.17)	3.66 (.15)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Confidence

Finally, a 2 (condition: high-penalty, low penalty) X 2 (group: NGs, RGs) mixed ANOVA on participants' confidence ratings did not reveal any group differences. There were no main effects or an interaction, largest $F(1,56) = 1.01$, $p = .32$.

Summary

Experiment 1 explored the decision-making behaviour of RGs and NGs using a simplified blackjack task. Penalties for FAs (incorrect gambles) were manipulated across two conditions: a high-penalty condition and a low-penalty condition. SDT was applied to the analysis to separate three main performance parameters: accuracy, resolution and bias. Confidence ratings across the conditions were also explored.

The results demonstrated that participants were sensitive to the bias manipulation. Participants shifted their gambling criteria between the two conditions and set a much more liberal criterion in the low-penalty condition, which resulted in a higher total score. The findings also showed that the RGs demonstrated better resolution than the NGs across both conditions. However, this resolution difference was not large enough to lead to a difference between the groups' total scores, perhaps because the accuracy and gambling criterion performances were very similar, and these two components may contribute more to total score than resolution alone.

The findings support the gambling expertise hypothesis. It appears that through regular gambling, the RGs can learn when a decision is more advantageous, despite only very general gambling backgrounds that incorporated both skill- and chance-based games. No participants who took part regularly gambled solely on blackjack, and some participants did not report playing blackjack at all. In contrast, the NGs do not have this gambling experience so their resolution is much lower.

However, there are some limitations of the blackjack task, which may have prevented the detection of further group cognitive and metacognitive differences. First, the game was too simplistic; a lot of the features were removed through simplification of the game, such as the option to 'split' and place 'insurance bets'. Participants also only had the opportunity to play the very first round of the game. This simplification resulted in the decision (advantageous/ disadvantageous) being too easy to answer correctly, leading to a near ceiling effect with very high accuracy rates achieved by both groups. Further differences between the groups may have become apparent if the game had been more complex. Considering blackjack in real life, it is the ‘additions’ of the game of blackjack, and more specifically, the decisions that are made after the first round, that makes the game exciting and appealing to gamblers, and determines how much one wins or loses. These features were removed from the present experiment, and so participants experienced very few risks, and the ecological validity was reduced.

Second, and perhaps more importantly, the experiment did not have clearly defined right versus wrong decisions. As only the first round was played it was difficult for the participants to determine whether the decision to hit/hold was advantageous in the long run. Success in blackjack, like all gambling, relies on taking some risks and a disadvantageous decision could turn into an advantageous decision (and vice versa) depending on which cards are dealt next to both the player *and* the dealer in the following rounds.

Finally, whilst this experiment has been useful in demonstrating that RGs can better discriminate between their advantageous and disadvantageous decisions than the NGs, it is difficult to determine exactly which experiences are resulting in better resolution: it may be that previous blackjack experience contributed to better resolution; alternatively, it may be that the RGs’ experience with other gambling activities also contributed towards the RGs greater resolution.

A dice task, which is described in Experiment 2’s Method section (Chapter 3), was designed to address these concerns. The dice task has both probabilistic and deterministic outcomes, and appears to be much more sensitive to cognitive and metacognitive differences between different types of gamblers and non-gamblers.

CHAPTER 3
THE INTRODUCTION OF A NOVEL DICE TASK

Experiment 1 in Chapter 2 examined the decision-making of RGs and NGs in a simplified blackjack task with the manipulation of penalties. The results showed that regular gamblers are more discriminative than non-gamblers in their gambling decisions, but this resolution difference did not result in the RGs achieving a greater total score, as the accuracy and gambling criteria performances were comparable between the two groups.

In the present chapter, a novel gambling task was developed to address the limitations of Experiment 1 and to explore the RGs' and NGs' sensitivity to bias manipulations; more specifically, whether the skills that they acquire in regularly gambling could be *transferred*. The new task, a dice game, needed to be strategic and more difficult than the blackjack task so that ceiling effects could be avoided, and a clear correct versus incorrect stimulus decision could be defined. Manipulations of rewards and difficulty in the new task were examined in the experiments to follow.

Experiment 2
Reward Manipulation

Which factors modulate cognitive control? Factors that influence behaviour often fall into two main categories: emotional and reward motivational influences Chiew & Braver, 2011). Emotional factors may be accountable for the disruption or success of the cognitive system in optimally performing specific tasks, and may draw some individuals to gamble on a regular basis. For instance, Zuckerman (1979) proposed that individuals who gamble excessively try to maintain their optimal level of arousal. Zuckerman suggested that the sensation-seeking trait, evident in some individuals, could explain the differences in risk taking. Extending the idea of arousal, Anderson and Brown (1984) suggested that the excitement of gambling is a major reinforcer of gambling behaviour. Other research has proposed that problem gamblers can be divided into three subtypes which reflect their motivation to gamble. Blaszczynski and Nower (2002) proposed the Pathways Model which theoretically incorporated empirical knowledge of gambling behaviour from biological, personality, developmental, cognitive, learning theory and environmental factors into one framework. 'All three groups have common exposure to related ecological factors (e.g., availability, accessibility, and acceptability), cognitive processes and distortions, and contingencies of reinforcement. However, according to their proposed model, predisposing emotional stressors and affective disturbances for some individuals and biological impulsivity for others represent significant additive risk factors.' (Gupta, Nower, Derevensky & Blaszczynski, 2009, p. 10). Pathway 1 refers to individuals who gamble primarily for entertainment and socialisation; Pathway 2 refers to individuals who gamble as a means of escape, or are 'emotionally vulnerable' and present with anxiety and/or depression; and Pathway 3 distinguishes impulsive gamblers who may have attention deficits and antisocial personality traits. Other researchers have also established support for the differing subtypes of gamblers (e.g., Ledgerwood & Petry, 2006).

In contrast, motivation influences, which are studied through the introduction of rewards or penalties, are thought to strengthen goal pursuit and maintenance (e.g., Aarts, Custers & Veltkamp, 2008), and it is the influence of rewards on gambling cognitions and metacognitions that is the main focus of the present study. It is no secret that the gambling industry has researched and continues to employ various techniques that exploit the psychological impact of different reward manipulations, in particular, focusing on the emotional sources of motivation. For instance, some slot machines (also known as electronic gaming machines) are programmed to have frequent small payouts (often smaller than the original bets) to encourage gamblers to continue trying for a 'big win' (intermittent reinforcement). Research into 'continuous'[5] forms of gambling, such as slot machines and casino games, have been shown to have strong associations with problem gambling and are thought to more greatly influence the individual as the gambling involves 'very rapid cycles of stake, play, determination of outcome and opportunity to reinvest' (Clarke, Tse, Abbott, Townsend, Kingi & Manaia, 2006, p. 249; see also Dickerson, 1993; Griffiths, 1999). To illustrate, Breen and Zimmerman (2002) explored the elapsed time between the age of regular gambling and the age at which the DMS-IV pathological gambling criteria was first met in pathological gamblers. The findings demonstrated that gamblers who bet primarily on electronic gaming machines (a continuous form of gambling) met the DSM-IV criteria much earlier than individuals who bet on more

[5] Other games, such as lotteries and football pools, in which a significant time has elapsed between one bet and the next are known as 'discrete' games and are not so strongly associated with problem gambling (Walker, Schellink & Anjoul, 2008).

traditional forms of gambling, such as sports and horses. However, this study may be biased as all the gamblers who participated reported gambling problems prior to participation. But, clearly, some forms of gambling have different impacts on individual's involvement, and subsequent development of problem gambling.

Alternatively, the machines are programmed to allow gamblers to experience several 'near misses' (e.g., Cote, Caron, Aubert, Desrochers & Ladouceur, 2003), giving the illusion that the gambler is very close to winning. National Lotteries also work on the near-miss principle, with players expected to choose several small numbers from below 50, rather than pick one number from 14 million. These techniques reinforce gambling behaviours, and can lead some individuals to believe that previous gambles influence future ones (the gambler's fallacy; Ladouceur & Walker, 1996). Positive reinforcement of rewards can influence individuals to place more bets, or gamble for longer has also been researched. Walker and Schellink (2003, as cited in Zangeneh, Blaszczynski & Turner, 2007) estimated that the average gambler wins more money than invested in the early rounds of gaming machines. However, the experience of being ahead in the game creates a mentality that the jackpot will be won, so the individual maintains interest and ends the game at a loss.

In addition, neuroimaging studies have evidenced altered working memory and executive control performances due to reward manipulations (Gilbert & Fiez, 2004; Krawczyk, Gazzaley & D'Esposito, 2007). In a study by Savine and Braver (2010), the impact of performance-contingent reward incentives on neural activity was examined using a cued task-switching paradigm. Participants were cued to expect either gender targets (male or female) or syllable targets (two syllable words or not), and were required to make a classification of the target on both task-switching (in which the two cues were randomly intermixed) and single-task (same cue in every trial so the cue provided no information) blocks. Half of the trials involved incentives, which were cued to participants because dollar signs ($) surrounded the task cue. Rewards were given based on correctness of the classification and quick reaction time. The findings showed that behaviourally, the incentive trials resulted in significantly improved accuracy in the classification of the target stimulus, and enhanced the reaction times when task switching, highlighting the benefit of incentives when cognitive control demands were high.

It has generally been established that impairments in cognitive control are evident in individuals with psychiatric disorders, such as depression and schizophrenia (Pessoa, 2008; West, Choi & Travers, 2010). Consequently, Experiment 2 will examine the impact of reward manipulation on cognitive and metacognitive performance in a gambling task. This research may help to inform us about the decision-making advantages and/or shortcomings in the healthy human brain in relation to different rewards to determine the extent to which previous, non-problematic gambling experience results in greater control sensitivity in gambling tasks.

Study Overview

The first aim of Experiment 2 was to explore the suitability of a new computerised dice gambling task for examining cognitive and metacognitive variation between RGs and NGs. The secondary aim was to explore participants' sensitivity to the manipulation of rewards for Hits (*H*s, correct gambles).

Given a more difficult experiment than the previous, with definitive correct and incorrect answers, it was anticipated that greater performance differences between the RGs and NGs would be distinguished. Specifically, it was hypothesised that the RGs would demonstrate a greater sensitivity to the reward manipulation than NGs because the RGs have had regular experience of different reward and penalty structures. Based on the findings of Experiment 1, it was conjectured that the RGs would also demonstrate better resolution compared to the NGs. To test these hypotheses, participants were presented with a high-reward and a low-reward condition of a novel gambling task in Experiment 2.

Method

Participants

Participants who took part in Experiment 1 also participated in Experiment 2 (see Chapter 2 for detailed participant details). The experiments were counterbalanced to avoid order effects and there was no drop out between experiments.

Design and Materials

Participants completed the SOGS, HADs (see Appendices B & C) and demographics questionnaire if they were completing this experiment before the blackjack task (depending on the counter-balanced order of experiments).

A computerised gambling task inspired by Green and Swets (1966) was designed to resemble an actual dice-gambling game that may be played in a gaming venue/online. In this game, three dice are rolled 'virtually'. The first two dice are normal, yielding a value between 1 and 6. The third *unique die*, however, has 3 appearing on three faces and 0 appearing on the other three. On a given trial, the gambler sees only the sum of the three dice (between 2 and 15; see Figure 3.1 for the dice task trial layout presented to participants) and must indicate whether the 0 or the 3 was face-up on the unique die. Hence, if the displayed sum is 2, 3, or 4 on the one hand versus 13, 14, or 15 on the other, the correct responses are necessarily 0 versus 3, respectively. No other values of the unique die would be possible because the lowest sum for a 3 face on the unique die is 5 (1 + 1 + 3), whereas the highest sum for a 0 face is 12 (6 + 6 + 0). Other sums, however, do not have definitive answers but are probabilistic. For example, a sum of 8 is 56% likely to have a 0 face on the unique die.[6] See Table 3.1 for the probabilities of the unique die yielding a '3' for each sum presented to participants.

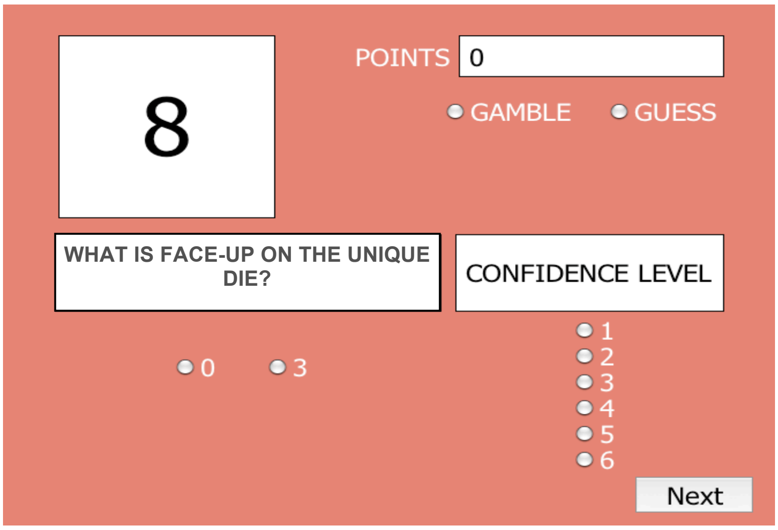

Figure 3.1. The dice task trial layout.

For each trial in each experiment, a computer algorithm sampled a sum with particular values of the three dice and the sum was presented to participants. Three selections were required on screen, as in Experiment 1. First, participants chose either a '0' or '3' response. Second, they decided whether to *gamble* or *guess* their 0/3 decision. If they chose to gamble their 0/3 decision and it was correct, points were

[6] Much of the description of the dice task in this chapter is altered from the published paper by Lueddeke & Higham (2011; see Chapter 4).

gained and added to their running total. However, if their 0/3 decision was gambled and it was incorrect, points were lost and deducted from the total.[7] If, instead, participants chose to guess, points were neither gained nor lost regardless of the accuracy of the 0/3 decision. The gamble versus guess decision is essentially akin to the bet versus fold decision needed in other games, such as poker, or the blackjack task of Experiment 1. Finally, a confidence rating was taken. The purpose of the game was to maximise the total number of points over trials.

Table 3.1

The Probabilities of the Unique Die Yielding a "3" for Each Sum Presented to Participants in Experiment 2.

Sum of 3 dice	Probability
2	0%
3	0%
4	0%
5	20%
6	29%
7	33%
8	44%
9	56%
10	67%
11	71%
12	80%
13	100%
14	100%
15	100%

Experiment 2 had a 'low-reward' and a 'high-reward' condition. In the low-reward condition, participants would gain 1 point for a correct gamble (H) and would lose 1 point for an incorrect gamble (FA). The high-reward condition meant that participants would gain 4 points for a hit and lose 1 point for a false alarm. No

[7] The number of points won or lost for a gamble decision varied between conditions, as explained in detail below.

rewards or penalties were credited to M (correct guess) or CR (incorrect guess) decisions.

Procedure

Participants were administered the two counterbalanced dice task conditions (low-reward; high-reward), either before or after participating in Experiment 1. The experiments were also counter-balanced to avoid order-effects. There was a break of five minutes between the two experiments.

Each condition contained 144 experimental trials and the trials were presented in a single random order to all participants. Participants were tested individually and full instructions on how to run the programme, the rules of the game, and what to do after completion of the task, were given to the participants. Participants were initially required to complete 5 practice trials to become accustomed to the dice task, which were similar to the actual task. The trials (both practice and test) included the presentation of the total sum of dice each trial. After this presentation, participants were required to make three selections on the computer (see Figure 3.1 for trial layout): 1) to decide whether they believed the unique die had landed on a '0' or '3'; 2) to decide whether they wanted to 'gamble' or 'guess' on that decision; and 3) to indicate their level of confidence (between 1 and 6) on the accuracy of their unique die decision. Once the first condition was completed, participants had a two-minute break and then began the trials for the alternative condition (another 144 trials). The trials were self-paced, and an additional break of two minutes was incorporated halfway through each set of trials (three breaks in total per task). Participants were given immediate feedback of their responses in the form of a 'points' box in the top right of the computer screen. The dice task lasted approximately 30 minutes.

Participants played for points instead of money as we wanted to discourage gambling after the tasks. However, an incentive of £20 worth of vouchers was also offered to the individual who scored the highest number of points across both tasks (the blackjack task and the dice task), in order to encourage more realistic gambling behaviour.

A debriefing statement revealing the main hypotheses of the experiment followed the gambling task. Information on where to seek help with gambling problems, if needed, was also supplied (although no participants were PGs).

Results

All performance measures were analysed using a 2 (condition: high-reward, low-reward) X 2 (group: RGs, NGs) mixed model ANOVA with condition as the within-participants variable and group as the between-participants variable, unless otherwise stated.

Total Scores and Accuracy

The total scores for each group in the different conditions are shown in Table 3.2. The mean scores do not appear to differ between the two groups, and this was confirmed by the mixed ANOVA showing no significant main effect of group on the total scores, $F < 1$. The analysis revealed a main effect of reward condition, $F(1, 48) = 1530.92$, $MSE = 2527.74$, $\eta_p^2 = .97$, $p < .001$, with higher scores achieved in the high-reward condition, as expected. There was no reward X group interaction, $F < 1$.

In order to determine how well the groups were regulating their accuracy, a 2 (condition: high-reward; low-reward) X 2 (accuracy type: overall accuracy; gambled accuracy) X 2 (group: RGs, NGs) mixed ANOVA analysed the data, with group as the only within participants variable. This analysis differed from the accuracy analysis in Experiment 1 because it was thought that exploring the accuracy of only gambled versus all decisions would allow us to observe how the participants were strategically regulating their accuracy. The overall accuracy refers to the accuracy obtained across all trials, whereas the gambled accuracy refers to the accuracy obtained for only the trials in which participants selected the gamble option (see formulae in Table 1.2 to calculate overall and gambled accuracy, and Table 3.2 for the accuracy means). The two sets of trials used in each of the conditions were the same (i.e., the sums presented to participants), but presented in a different order so it was no surprise that the main effect of condition was not significant, $F(1, 48) = .13$, $p = .72$. However, the analysis yielded a main effect of accuracy type, $F(1, 48) = 39.45$, $MSE = .001$, $\eta_p^2 = .45$, $p < .001$. Participants were more accurate with their gambled responses ($M = .73$; $SEM = .01$) than accuracy across all trials ($M = .69$; $SEM < .001$), indicating that they were able to strategically regulate their accuracy. The condition by accuracy type interaction was also significant, $F(1, 48) = 8.16$, $MSE < .001$, $\eta_p^2 = .15$, $p < .01$. The interaction was a result of a greater difference in overall and gambled accuracies in the low-reward condition (gambled accuracy: $M = .73$, $SEM = .01$; overall accuracy: $M = .69$, $SEM < .001$; mean difference = 4) compared to the high-reward condition (gambled accuracy: $M = .72$, $SEM = .01$; overall accuracy: $M = .70$, $SEM < .001$; mean difference = 2). The low reward meant that participants had to be extra cautious when selecting the gamble option as it would take longer to recoup the lost points if they were incorrect than the high reward condition. All other main effects and interactions were not significant, largest $F(1, 48) = 2.52$, $p = 12$.

Table 3.2
Means, standard deviations and ranges of the scores for the regular and non-gambler groups on the two reward conditions of Experiment 2.

		Condition	
Group		Low-Reward	High-Reward
NG	*M*	50.44 (1.90)	327.56 (8.80)
	Range	30.00 –63.00	168.00 – 401.00
RG	*M*	51.64 (2.20)	330.92 (12.67)
	Range	24.00 – 66.00	162.00 – 381.00

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Resolution

Many of the participants' HRs and FARs resulted in either 0 or 1, as in Experiment 1. Therefore, resolution performance was measured by *d* ' with the correction of 0.5 added to all contingency cells. The mixed ANOVA analysis on *d'* (see Table 3.3) did not result in any main effects or an interaction, largest $F = 2.87$, $p = .10$. However, there was a trend for the RGs ($M = .48$, $SEM = .04$) to have better resolution than the NGs ($M = .39$, $SEM = .04$), but this difference was not significant. The lack of group difference somewhat contrasts with the resolution findings of Experiment 1, but this may be due to the dice task being novel (see summary for further discussion).

Table 3.3

Accuracy, monitoring and bias means by group across the two reward conditions of Experiment 2.

	Performance Measure			
Group	Gambled Accuracy	Overall Accuracy	Resolution (*d′*)	Gambling Criterion (*c*)
	Low-Reward Condition			
NG	.72 (.01)	0.69 (.01)	0.42 (.05)	-1.21 (.19)
RG	.74 (.01)	0.69 (.01)	0.50 (.05)	-0.98 (.19)
	High-Reward Condition			
NG	.71 (.01)	0.69 (.01)	0.36 (.06)	-1.56 (.19)
RG	.73 (.01)	0.70 (.01)	0.47 (.06)	-1.62 (.19)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers

Gambling Criterion and Bias Profiles

The 2 X 2 mixed ANOVA on *c* (see Table 3.3 for means) revealed a significant main effect of condition, $F(1, 48) = 20.64$, $MSE = .30$, $\eta_p^2 = .30$, $p < .001$, which demonstrated that participants were responding more conservatively in the low-reward condition ($M = -1.10$, $SEM = .14$) compared to the high-reward condition ($M = -1.59$, $SEM = .13$), as expected. This is a similar finding to the criterion shift that was observed in Experiment 1. A main effect of group and the interaction were not significant, largest $F = 1.79$, $p = .19$.

Although informative with respect to some aspects of performance, the analyses conducted thus far have not given any indication of how RGs and NGs *should* have behaved to maximise their point total. There is an optimal criterion setting that is likely to maximise the final score. Deciding to gamble too often in this gambling task (and many others) can lead to a loss of points because inaccurate 0/3 decisions garner the penalty. However, guessing too often also has its problems because participants lose out on possible points that would have been gained if the accurate 0/3 decisions had been gambled. Thus, a way to determine how an individual is actually performing (actual bias) compared to how they should optimally be performing (optimal bias) can be illustrated by creating a *bias profile*. Bias profiles hold the same assumptions as the type-2 SDT model used in this thesis: that the correct and incorrect decisions are normally distributed over confidence and that they have equal variance (see Chapter 1 for a discussion). Higham (2007) demonstrated that this model could adequately predict performance on formula-scored tests.

A bias profile is a plot of the corrected score as a function of the proportion of 'guess' responses (see Higham, 2007; Higham & Arnold, 2007a). The corrected score in this dice task can be calculated by the following formula:

[number of correct gambles x reward] – [incorrect gambles x penalty]

Higham (2007) stated that three distinct parameters are required to create a bias profile: resolution (d'), the overall accuracy (gambles + guesses), and the penalty for errors. In the present experiment, and the experiments to follow, the reward for correct responses is another parameter that needed to be taken into consideration. The mathematical formulae to create bias profiles from these parameters, and optimal bias, are shown in Appendix A.

The mean type-2 Hs (correct gambles), FAs (incorrect gambles), Ms (correct guesses) and CRs (incorrect guesses) frequencies were taken for each group and the methodology was applied to create one bias profile for each group in each condition (see Figures 3.2 and 3.3). Consider Figure 3.2, whereby a separate curve (profile) has been created for each group in the low-reward condition. Across the x-axis is the 'proportion of guesses', that is, the proportion of trials that the group has, or should have, selected the guess option. Along the y-axis is the 'corrected score', which refers to the total score after the rewards and penalties, have been applied. The non-gamblers' mean resolution and mean accuracy, along with the reward for Hs (+1) and penalty for FAs (-1) parameters was input into the bias profile methodology which generated the bottom curve in Figure 3.2 (the thinner black line). The methodology is quite intuitive: if we consider the far right of this curve, the corrected score is 0 as all trials would have been guessed on (extreme conservatism, Higham & Arnold, 2007a), and only trials that are gambled on can garner a reward or penalty in this task. Focusing on the other extreme, the far left of the curve, no trials would have been guessed on (extreme liberalism), but the maximum corrected score in which the non-gamblers would be able to achieve is 0.35. The highest point on the curve represents optimal bias, that is, an individual's ideal criterion setting in order for him or her to gain the maximum number of points based on their accuracy and resolution performance. Thus, the triangular marker on the thin curve represents the non-gamblers' optimal bias. Actual bias can also be plotted on the same graph and the square marker depicts how the non-gamblers have set their actual bias. From this curve, it can be seen that had the non-gamblers selected the guess option only 1.3%, as opposed to 18%, of the trials, they would have gained a greater corrected score.

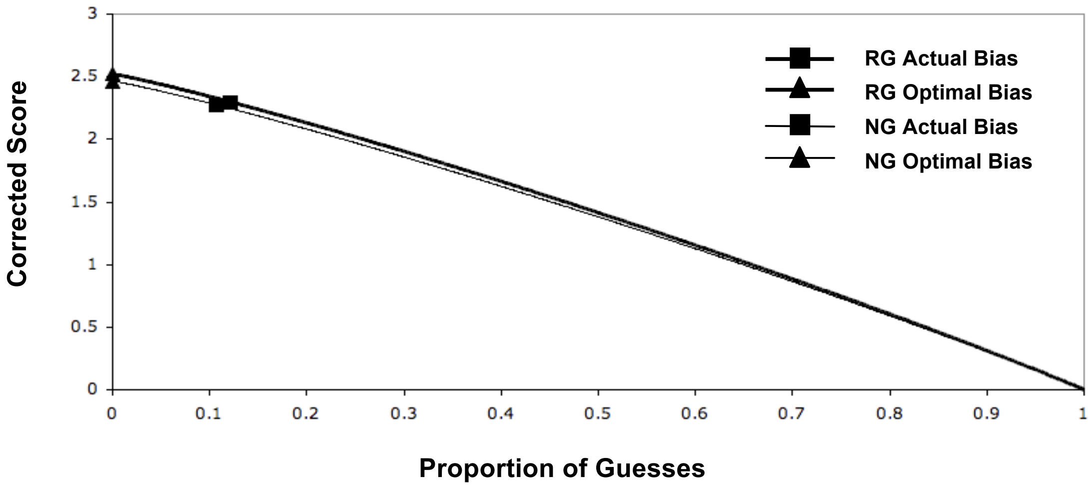

Figure 3.2. Bias profiles for regular and non-gamblers in the low-reward condition. RG = regular gamblers, NG = non-gamblers.

The RGs' bias profile (the thick black line) is slightly more raised because they have marginally better resolution performance (even though this is not significant, see Resolution analysis). Similar to the NGs, the RGs are gambling too conservatively for the demands (rewards and penalties) of the task, and their accuracy and resolution performances, and the RGs' optimal bias (4% of guesses) is set to the left of their actual bias (21% of guesses). Had the RGs selected the gamble option more often, they too would have completed the low-reward condition with a greater score (0.38 as opposed to 0.36). In sum, both groups are deviating at similar distances from optimal bias and they should have gambled almost all of the time in order to optimise their scores.

Figure 3.3 demonstrates the bias profiles for the RGs and NGs in the high-reward condition. The profiles show a greater corrected score (both actual and optimal score) than the low-reward condition (Figure 3.2), because the reward associated with Hs was much greater (+4). The bias profiles indicate that, again, both groups are deviating substantially from their optimal bias and they are gambling too conservatively. In this condition, participants should be selecting the gamble option 100% of the trials as they are limiting their optimal score by selecting the guess option too often. The RGs' performance is not differing from the NGs' in either of the conditions, unlike the sensitivity that was found in Experiment 1.

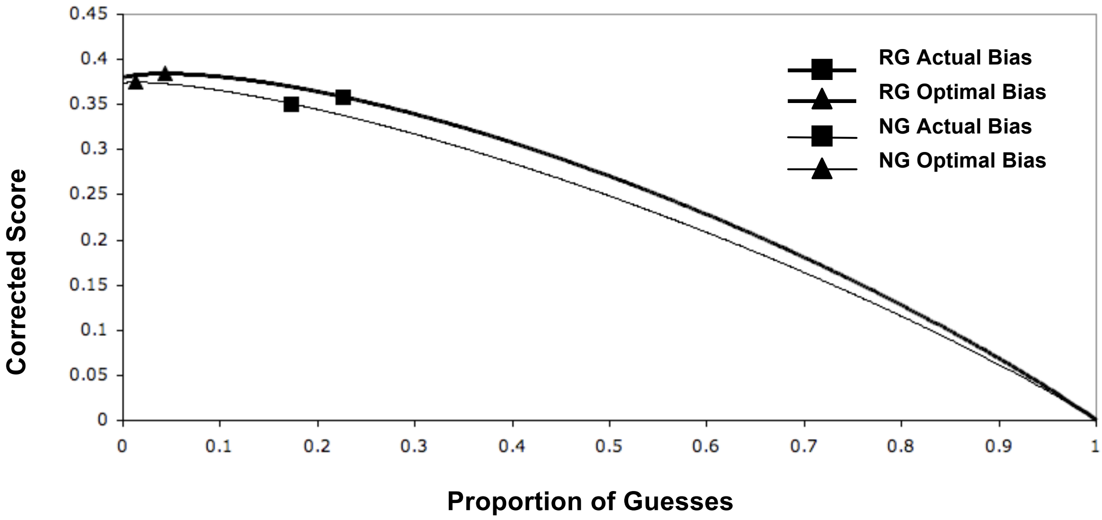

Figure 3.3. Bias profiles for regular and non-gamblers in the high-reward condition. RG = regular gamblers, NG = non-gamblers.

Analysis of Individual Sums. The bias profile methodology can also be used to determine how each group was responding to individual sums as opposed to participants' responses to all sums, that was displayed in Figures 3.2 and 3.3. This analysis is potentially very useful as each of the sums presented to participants have different underlying probabilities (see Table 3.1) and it will be possible to observe whether the groups are gambling differently depending on the sums.

Hence, the data was split into Hs, FAs, Ms, and CRs for each *individual* sum (ranging from 2 to 15) presented during the gambling task. From these four frequencies per sum, both the optimal bias profiles and empirical gambling likelihoods (as calculated in Table 1.2; an alternative measure for actual bias) for RGs and NGs were calculated and plotted in Figures 3.4 (low-reward condition) and 3.5 (high-reward condition). Gambling likelihood is an intuitive measure of bias because the more an individual selects the gamble option, the more liberal he/she is gambling (see Chapter 4 for an experiment that utilises the gambling likelihood measure). However, this measure has been subsequently criticised in Chapter 5 as it potentially can be influenced by measures of accuracy and resolution.

The Individual Sum Plots in Figures 3.4 and 3.5 show the proportion that each group selected the 'gamble' option per sum. The solid bold line refers to the RGs' actual bias performance, the dashed bold line refers to the NGs' actual bias performance, and the thin solid and dashed lines refer to the RGs and NGs optimal bias performances, respectively. In Figure 3.4 (low-reward condition), the optimal gamble proportions suggest that the participants should be gambling almost 100% of the time, except on the sums of 8 (for the RGs) and 9 (for the NGs) on which they should not have gambled at all. The actual gambling likelihoods indicate that both groups are treating the ambiguous sums between 5 and 12 differently than the definitive sums (2-4 and 13-14), but they are generally too conservative.

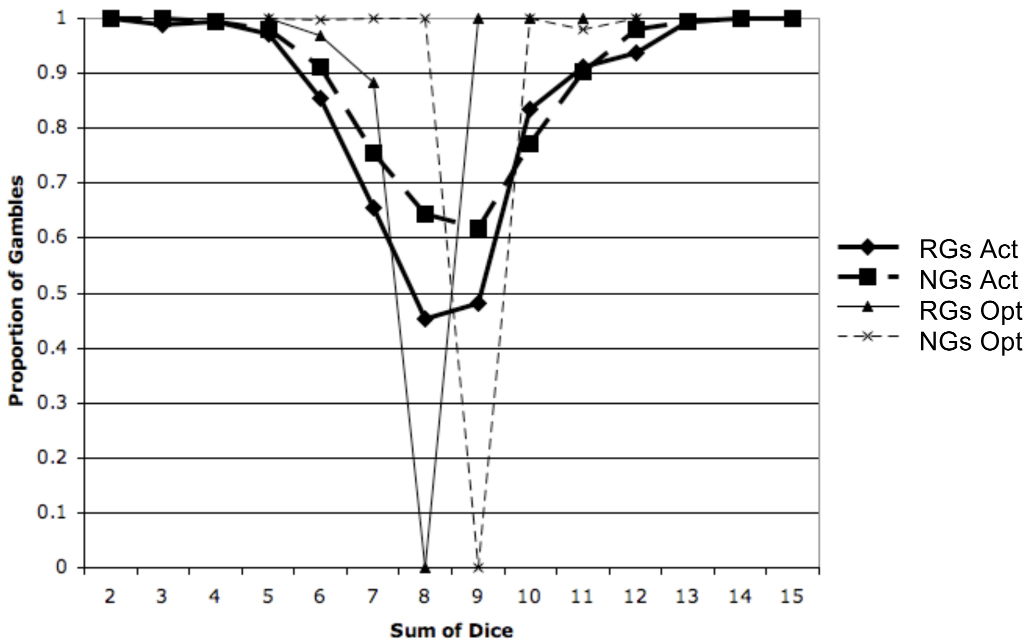

Figure 3.4. The proportion of gambles across each of the presented sums in the gambling task of both groups in the low-reward condition. RGs = regular gamblers; NGs = non-gamblers; Act = actual proportion of gambled responses per sum; Opt = optimal proportion of gambled responses per sum.

The optimal bias across all sums in Figure 3.5 suggests that both groups should not select the guess option for any sum, which supports the bias profile of Figure 3.3. Both groups are, again, gambling too conservatively across the ambiguous sums.

Furthermore, the bias shift (main effect of condition on *c*) can be clearly observed between these two figures, with participants gambling more liberally in the high-reward condition. To illustrate, the RGs and NGs are gambling approximately 75% of the time on the sums of 8 and 9 in the high-reward condition (Figure 3.5), but they are gambling approximately 45% (RGs) and 63% (NGs) of the time on the sums of 8 and 9 in the low-reward condition (Figure 3.4).

To conclude, both the RGs and NGs are responding to individual sums very similarly in the high-reward condition, but the RGs are slightly more conservative with the sums of 8 and 9 in the low-reward condition.

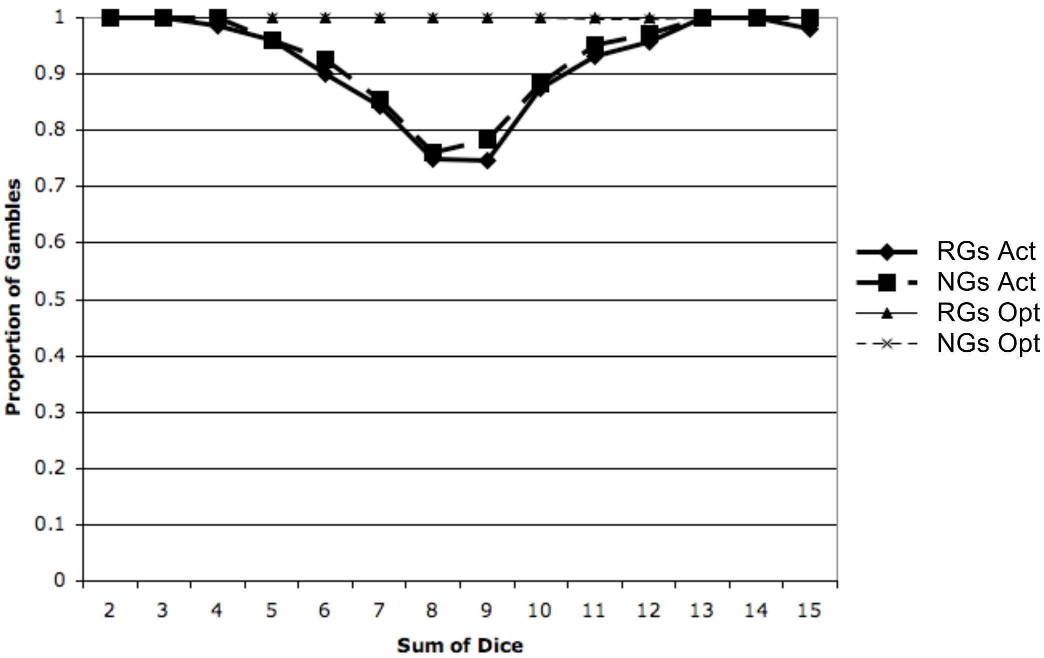

Figure 3.5. The proportion of gambles across each of the presented sums in the gambling task of both groups in the high reward condition. RGs = regular gamblers; NGs = non-gamblers; Act = actual proportion of gambled responses per sum; Opt = optimal proportion of gambled responses per sum.

Summary

Experiment 2 investigated the decision-making strategies of regular gamblers and non-gamblers when presented with low- and high-reward conditions of a dice gambling task. It was anticipated that the RGs would be more sensitive to the manipulation of rewards because of their prior experience on gambling tasks. More specifically, it was hypothesised that the RGs would have better resolution and more effective gambling control than the NGs. The hypotheses were not supported by the analyses, with no significant group differences observed for each of the cognitive and metacognitive measures. These results contrast with the findings of Experiment 1, in which the RGs demonstrated better resolution than the NGs.

Both groups were able to shift their gambling criterion between the two conditions, with a more liberal criterion set for the high-reward condition. Whilst this shift appears intuitive, in examining the bias profiles, both conditions actually required a very similar proportion of guesses to perform optimally, and therefore, the participants were generally overcompensating (gambling too conservatively) for the change in rewards. More specifically, the Individual Sum Plots indicated that participants were too conservative when gambling on ambiguous sums between 5 and 12 in both the high-reward and low-reward conditions. However, the RGs and NGs were overconfident (too liberal) when gambling on the sums of 8 and 9, respectively, of the low-reward condition.

The findings suggest that RGs are not more sensitive than NGs to the manipulation of rewards in terms of both resolution and gambling control. It may be that the reward manipulation does not have the same effect on participants as the manipulation of penalties that was observed in Experiment 1. Perhaps the high penalty of Experiment 1 had pre-occupied the NGs and so they found it more difficult than the RGs to discriminate between their correct and incorrect decisions. However, it is difficult to generalise as a different task was utilised in this experiment. The experiment used a novel dice task that participants had not played prior to taking part. It may be that the experience advantage that the RGs portrayed in Experiment 1 could not be transferred to a novel task in the present experiment.

An alternative explanation could be that the parameters of this task were not extreme enough to detect a difference between the groups. It is evident in comparing the bias profiles of the two conditions that the optimal bias markers are in very similar places. If there had been greater scope for the participants to shift their gambling criterion then more differences between the groups may have been observed. Another experiment exploring the role of rewards on decision-making using a more extreme payout structure (i.e., keeping a higher penalty constant whilst manipulating the rewards) would be useful to determine if there are further differences between the groups with a reward manipulation. To verify which explanation is the most likely, another reward manipulation experiment was conducted with different payout structures and the details and results of the new reward experiment can be found in Chapter 4 (Experiment 4).

Experiment 3
Difficulty Manipulation

The previous two experiments explored the decision-making of RGs and NGs with manipulations of penalty and reward. Another way to manipulate bias is by changing the difficulty of the task, which is the focus of the present experiment. Young and Bentall (1997) explored the manipulation of task difficulty on response bias in a probabilistic reasoning study on deluded, depressed, and normal control participants. In the first experiment, the participants were presented with two bags of twenty green and yellow beads. The proportions of each colour were manipulated to create easy and difficult conditions. The beads were withdrawn from view and participants were required to indicate (on a 7-point scale) their certainty that a series of beads had been drawn from one of the two bags. Participants' willingness to 'jump to conclusions', that was, for them to say with certainty that the beads were drawn from a particular bag, was calculated for each group. Young and Bentall found that participants were able to shift their response bias between the easy and difficult conditions, with participants more willing to jump to conclusions in the easy condition. The second experiment used a similar task with more meaningful stimuli and participants had to judge whether personality characteristics described one of two individuals. The results also showed that the meaningful stimuli led participants to jump to conclusions more quickly than the bead stimuli, but participants also more quickly revised their certainty estimates downwards when presented with disconfirmatory evidence. Further, compared to controls, the clinical participants (deluded and depressed) were more willing to give a certainty rating when presented with both neutral (beads) and meaningful (personality) stimuli, which the researchers suggest is a result of reasoning deficits.

Study Overview

The main research question that we wanted to address in the current study was: to what extent does the manipulation of difficulty impact on gambling decision-making of regular and non-gamblers? Participants were presented with two conditions of the dice task. By varying the frequency of ambiguous (probabilistic, sums 5-12) and deterministic (definite right and wrong answer, sums 2-4 and 13-15) sums, ‘difficult’ and ‘easy’ conditions were created. We hypothesised that both groups would be sensitive to the manipulation and shift their gambling criterion between the two conditions, with a more liberal criterion selected for the easy condition.

There was some uncertainty whether we would observe any differences between the RGs and NGs, as the previous two experiments demonstrated inconsistent findings. Specifically, Experiment 1 demonstrated the RGs’ greater resolution performance than the NGs on a well-known, but simplified blackjack task. Experiment 2 did not find any cognitive or metacognitive differences between the RGs and NGs on a novel gambling dice task. A hypothesis for the present experiment was that the RGs were unable to transfer skills gained during their regular gambling experience to a task that they had not played. As gambling consists of a series of chance occurrences, even in games that incorporate some element of skill (such as blackjack or poker), the unpredictability of gambling outcomes may compromise or mitigate against skill transference to novel gambling tasks.

On the other hand, if it is found that statistically the RGs are indeed more sensitive to the difficulty manipulation compared to the NGs, then a case may be made that expertise gained through regular gambling practice can be transferred to novel gambling tasks, thereby potentially confirming the expertise-transference hypothesis.

Method

Participants

Twenty-five RGs and 25 NGs aged between 18 and 33 years (M = 22.02; SD = 3.59) participated in the experiment. A total of 14 females and 36 males (staff, and current or previous students) volunteered to participate after viewing an advertisement on the University of Southampton’s ‘Classifieds’ website. RGs were classified as individuals who gambled at least once a month on any gambling activities that involved money, such as going to casinos, betting shops, bingo, gaming venues or playing online or with friends. Participants who scored 3 or above on the SOGS (Appendix C) were excluded from the study, as they were potentially PGs and non-problem gamblers were the main focus. The majority of participants completed the experiment in a research laboratory on campus, but the dice-game was also sent to 30% of the participants by email to gain access to a greater number of people. There were no differences in the results between the data completed in the lab and the data completed at the individual's home/at their own convenience. Participants were offered £5 as an incentive for completing the study. Additionally, an incentive of £20 worth of vouchers was offered to the highest scoring individual.

Table 3.4

Frequencies of the Sums, 0 Trials, and 3 Trials Presented to Participants across the Conditions of Experiment 3.

Sum	Easy Condition						Difficult Condition					
	NG			RG			NG			RG		
	N	0	3	N	0	3	N	0	3	N	0	3
2	5	5	0									
3	5	5	0	10	10	0	3	3	0			
4	18	18	0	16	16	0	6	6	0	6	6	0
5	9	7	2	10	8	2	5	4	1	6	5	1
6	6	4	2	6	4	2	8	6	2	6	4	2
7	8	5	3	8	5	3	18	12	6	16	11	5
8	7	4	3	8	4	4	18	10	8	24	13	11
9	7	3	4	8	4	4	18	8	10	24	11	13
10	8	3	5	8	3	5	18	6	12	16	5	11
11	6	2	4	6	2	4	8	2	6	6	2	4
12	9	2	7	10	2	8	5	1	4	6	1	5
13	18	0	18	16	0	16	6	0	6	6	0	6
14	5	0	5	10	0	10	3	0	3			
15	5	0	5									
Total	116			116			116			116		

Note: With random sampling, the 0 face is more likely for sums 1-8, whereas the 3 face is more likely for sums 9-15. RG = regular gamblers; NG = non-gamblers; N = Total number of trials presented with given sum; 0 = Number of trials of a given sum with '0' face on unique die; 3 = Number of trials of a given sum with '3' face on unique die.

Design and Materials

The HADs (Appendix B), SOGS (Appendix C) and demographic questionnaires were given to the participants prior to completion of the dice task. Bias was manipulated by altering the difficulty of the task. The number of trials defined the easy and difficult conditions with extreme (definitive) versus moderate (ambiguous) sums (see Table 3.4). For the easy condition, many trials consisted of 2s, 3s, and 4s (for which the 0 face was 100% likely) as well as 13s, 14s, and 15s (for which the 3 face was 100% likely). Conversely, the difficult condition contained more moderate, ambiguous sums such as 7s, 8s, 9s and 10s. For these sums, the most likely answer is less obvious, and even if it is chosen, it is less likely to be accurate. For example, with random sampling, 56% of the 9 sums will be generated by a 3 face on the unique die on average. But even if this most likely 3 face is chosen every time the 9 sum is shown (which is the wisest strategy), accuracy will only average out to 56%.

As before, participants were required to make three selections on each trial screen: to make a decision (did the unique die land on a 0 or a 3?); to state whether to gamble or guess based on that decision; and to select a confidence rating between 1 and 6 (with 6 being the highest level of confidence in the accuracy of the 0/3 decision).

Pilot Study[8]. Before running this study, a pilot study was carried out on forty participants (one group of 20 RGs; one group of 20 NGs) to determine whether there were any accuracy differences between the groups due to their different levels of experience with gambling tasks. The pilot study presented participants with 288 trials of the dice gambling task. Participants were rewarded 1 point for a H and lost 2 points for a FA. The pilot study highlighted that despite the accuracy findings of the reward experiment, the RGs were significantly more accurate than the NGs (greater accuracy of RGs was also observed in Experiments 4 and 5 in Chapter 4), but there were no observed differences in either resolution or gambling control between the groups. However, because accuracy (difficulty) was the main independent variable in the present experiment, it was necessary to equate the groups for accuracy in case it confounded interpretation of the results, or resulted in observed resolution/bias differences that were actually attributed to accuracy.

[8] The pilot study formed part of an MSc Research Methods in Psychology project and does not contribute to the present degree.

Therefore, an 'easy' block of trials and a 'difficult' block of trials was created using slightly different sums for the RGs and NGs. The sums were chosen so that the *expected* accuracy for a block of a given condition (as a whole) would be equal between the two groups of participants. This selection process effectively meant that NGs were presented with a greater proportion of extreme (easier) sums than RGs within a given block of trials. Table 3.4 shows the sums presented to each group in Experiment 3, as well as the number of 0 versus 3 faces that made up each sum.

In all cases, the distribution of 0 versus 3 faces was kept as close as possible to the expectation based on random sampling of the dice faces. By manipulating the presented sums in this way, accuracy for RGs and NGs was expected to be 80.1% and 80.4% in the easy condition and 63.8% and 63.3% in the difficult condition, respectively. The pilot study also revealed that the penalty for FAs was not severe enough; both groups of participants were tending to gamble too often, as evident by the bias profiles. Consequently, the reward for Hs and the penalty for FAs were increased to +2 points and -5 points, respectively, in Experiment 3.

Procedure

The research protocol was reviewed and approved by the University of Southampton's Psychology Ethics. The SOGS was emailed initially to all volunteers to check their eligibility to participate. Individuals who qualified for the study (i.e., gambled on a regular basis without reporting a gambling problem, or did not gamble at all) were assigned to one of the two experimental conditions. The participants were then given or sent (if they were participating over email) an informed consent form along with questionnaires asking demographic details, and the HADS.

The computer-based tasks were then administered in a counter-balanced order with half of the participants in each group participating in the 'difficult' condition followed by the 'easy' condition, and the other half participating in the conditions in the reverse order. Each condition contained 116 experimental trials and the trials were presented in a single random order to all participants. Participants were tested individually and full instructions on how to run the programme, the rules of the game, and what to do after task completion, were given to the participants. Participants were initially required to complete 5 practice trials to become accustomed to the task. These trials were similar to the actual task. The trials (both practice and test) included the presentation of the total sum of dice each trial. After this presentation, participants were required to make three selections on the computer: 1) to decide whether they believed the unique die had landed on a '0' or '3'; 2) to decide whether they wanted to 'gamble' or 'guess' on that decision; and 3) to indicate their level of confidence (between 1 and 6) on the accuracy of their unique die decision. Once the first condition was completed, participants had a two-minute break and then began the trials for the alternative condition (another 116 trials). Participants were given immediate feedback of their responses in the form of a 'points' box in the top right of the computer screen.

It was thought that playing for money might encourage gambling behaviour after participation in the task, which we wanted to avoid, so participants played for points instead. However, as before, an incentive of £20 worth of vouchers was also offered to the individual who scored the highest number of points across both tasks.

A debriefing statement revealing the main hypotheses of the experiment followed the experiment, as well as information as to where to seek help with gambling problems (although no participants were PGs).

Results

Ninety-eight percent of the participants had an undergraduate degree or higher, with one individual educated up to college level. The RGs were asked their most preferred games on which to gamble (listing up to five), and 83% of the sample enjoyed sports/horse betting; 67%, poker; 33%, blackjack or other card games; 17%, roulette or slot machines; and 5%, other games such as chess and mah-jong. RGs obtained an average score of 1.76 on the SOGS. None of the participants indicated that they were depressed or anxious, as measured by the HADS.

2 X 2 Analyses of Variance (ANOVAs) were conducted on the each of the measures, unless otherwise stated. Each ANOVA was mixed with group (NGs, RGs) and difficulty (easy, difficult) as between- and within-participant variables, respectively. A Type-2 SDT framework was implemented to investigate the main components of group performance, which include total score, accuracy, resolution, and gambling criterion. Analyses of confidence and optimal criterion setting across individual sums are also included.

Table 3.5

Means, and Ranges of the Total Scores for Regular Gamblers and Non-gamblers in the Two Difficulty Conditions of Experiment 3.

		Experimental Condition	
Group		Easy Condition	Difficult Condition
NG	*M*	88.44 (5.06)	1.28 (7.67)
	Range	35.00 – 122.00	-97.00 – 53.00
RG	*M*	93.28 (3.55)	6.68 (5.90)
	Range	51.00 – 118.00	-73.00 – 36.00

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Total Scores and Accuracy

Total scores were computed as in Table 1.2. The data (means and SEs) for each of the groups across the two conditions are reported in Table 3.5. A 2 X 2 ANOVA on the total scores revealed a main effect of condition, $F(1, 48) = 420.55$, $MSE = 448.70$, $\eta_p^2 = .90$, $p < .001$; as expected, the scores were considerably higher in the easy condition (M =90.86, SEM =3.09) compared to the difficult condition (M = 3.98, SEM = 4.84). The main effect of group and the interaction between difficulty and group were not significant, both $Fs < 1$.

Accuracy across all trials (overall accuracy) and on gambled trials (gambled accuracy) was computed for each participant (see Table 1.2 for the formulas and Table 3.6 for the means and SEs). A 2 X 2 X 2 mixed ANOVA was conducted on the data, with group (NGs, RGs) as the between-participants variable and condition (easy, difficult) and accuracy type (overall, gambled) as the within-participants variables. The ANOVA yielded a main effect of condition, $F(1, 48) = 405.75$, $MSE = .00$, η_p^2 = .89, $p < .001$, with higher accuracy in the easy condition (M = .83, SEM = .01) compared to the difficult condition (M = .70, SEM = .01). There was also a main effect of accuracy type, $F(1, 48) = 93.18$, $MSE = .00$, $\eta_p^2 = .66$, $p < .001$. Gambled accuracy (M =.81, SEM = .01) was significantly better than overall accuracy (M = .72, SEM = .00). This finding suggests that individuals were gambling on sums for which the 0/3 decision was most accurate, indicating that participants as a whole were able to strategically enhance their accuracy using the gamble option; a finding that was also demonstrated in Experiment 2. Importantly, there was a group X accuracy type interaction, $F(1, 48) = 4.37$, $MSE = .02$, $\eta_p^2 = .08$, $p = .042$. The interaction demonstrated that RGs strategically enhanced their accuracy better than the NGs. That is, there was a greater difference between the overall accuracy and gambled accuracy for the RGs, (overall accuracy: $M = .71$, $SEM = .01$; gambled accuracy: RGs $M = 0.82$, $SEM = .01$) compared to NGs (overall accuracy: $M = .73$, $SEM = .01$; gambled accuracy: $M = 0.80$, $SEM = .01$). No other main effects or interactions were significant, largest $F = 3.01$, $p > .05$. These findings support that the attempt to equate the RG and NG accuracies was successful.

Table 3.6

Mean Overall Accuracy, Gambled Accuracy, Resolution and Gambling Criterion as a Function of Group and Difficulty Condition in Experiment 3.

Group	Measure				
	Overall Accuracy	Gambled Accuracy	Resolution	Gambling Criterion	Deviation[9]
	Easy Condition				
NG	0.79 (.01)	0.86 (.01)	0.98 (.11)	-0.83 (.19)	.13 (.02)
RG	0.79 (.01)	0.88 (.01)	1.09 (.11)	-0.47 (.19)	.14 (.02)
	Difficult Condition				
NG	0.67 (.01)	0.74 (.02)	0.48 (.07)	-0.62 (.21)	.36 (.05)
RG	0.64 (.01)	0.76 (.02)	0.59 (.07)	-0.09 (.21)	.26 (.05)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Resolution

Thirteen (5 RGs and 8 NGs) of the participants' data resulted in undefined HRs and FARs. Therefore, the correction of 0.5 was added to all cells (Hs, FAs, Ms,

[9] This measure refers to the groups' absolute deviation from optimal bias.

CRs), as in the previous two experiments, before running the analysis on d'[10] (see Table 3.6 for the resolution means).

A 2 X 2 ANOVA on d' revealed a main effect of condition, $F(1, 48) = 41.31$, $MSE = .15$, $\eta_p^2 = .46$, $p < .001$, with participants able to discriminate accuracy better in the easy condition ($M = 1.03$, $SEM = .08$) than the difficult condition ($M = .54$, $SEM = .05$). Generally, participants tended to know how to gamble more effectively when presented with easier sums. For example, if a '4' was presented, they would nearly always 'gamble' correctly on the unique die having landed on a '0' (100% chance of this occurring). In contrast, correctly monitoring the accuracy of a '0' versus '3' decision to a sum of '9' (with only 56% chance of the unique die having landed on a '3') was much more difficult. Neither the main effect of group nor the difficulty by group interaction was significant, $F(1, 48) = 1.20$, $MSE = .25$, $\eta_p^2 = .02$, $p = .28$, and $F < 1$, respectively.

Confidence Analysis

Above, resolution was examined by analysing participants' ability to discriminate between correct versus incorrect 0/3 decisions using the gamble/guess option. However, it is also possible to examine metacognitive monitoring using rated confidence and determining how well it predicts accuracy (see Table 3.7 for the confidence means and SEs). Hence, a 2 (group: RGs, NGs) X 2 (condition: easy, difficult) X 2 (accuracy: correct, incorrect) mixed-factorial ANOVA on mean confidence was conducted[11]. Group was the only between-participants variable. A main effect of condition was revealed, $F(1, 48) = 16.89$, $MSE = .30$, $\eta_p^2 = .26$, $p < .001$, with higher mean confidence in the easy condition ($M = 3.89$, $SEM = .12$) compared to the difficult condition ($M = 3.57$, $SEM = .12$;).

[10]A 2(group: RGs, NGs) X 2(condition: easy, difficult) mixed ANOVA on resolution (d') was also conducted on the uncorrected data ($n = 37$), which resulted in similar findings to the resolution analysis reported. Only the main effect of condition was significant, $F(1, 35) = 63.91$, $MSE = .20$, $\eta_p^2 = .65$, $p < .001$.

[11]A 2 (group: RG, NG) X 2 (condition: easy, difficult) X 2 (gamble option: gamble, guess) X 2 (accuracy: correct, incorrect) ANOVA would have been preferred on the confidence data to observe how confidence varied depending on gamble option, and to further support the resolution findings. However, this analysis was not possible because of empty cells.

Table 3.7

Mean Confidence Ratings For Regular Gamblers and Non-Gamblers as a Function of Confidence Type and Difficulty Level in Experiment 3.

	Confidence Type	
Group	Correct Confidence	Incorrect Confidence
	Easy Condition	
NG	4.15 (.18)	3.58 (.20)
RG	4.19 (.18)	3.65 (.20)
	Difficult Condition	
NG	3.73 (.16)	3.37 (.18)
RG	3.79 (.16)	3.39 (.18)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Participants also assigned higher confidence to their correct decisions, which was reflected in a main effect of accuracy on confidence, $F(1, 48) = 61.36$, $MSE = .18$, $\eta_p^2 = .56$, $p < .001$ (correct $M = 3.96$, $SEM = .11$; incorrect $M = 3.50$, $SEM = .12$). This finding demonstrates that both groups were monitoring above chance, consistent with moderately sized *d'*s reported in Table 3.6. Importantly, the group by accuracy interaction was not significant, $F < 1$, indicating that monitoring was comparable between RGs and NGs. This result confirms the analysis on *d'*. No other effects were significant, all *Fs* < 1.

Gambling Criterion

Bias was estimated using *c*, computed for each participant on the corrected data (see Table 1.2 for the formula and Table 3.6 for means and SEs of *c*). A significant main effect of condition was revealed, $F(1, 48) = 12.90$, $MSE = .17$, $\eta_p^2 = .21$, $p = .001$, which demonstrated more liberal gambling in the easy condition ($M = -.65$, $SEM = .13$) than in the difficult condition ($M = -.35$, $SEM = .15$), as expected. Both the RGs and NGs were able to adjust their gambling criterion to a more conservative position to deal with the higher percentage of moderate sums presented in the difficult condition. Despite the bias means appearing substantially different between the groups, the main effect of group was not significant, $F(1, 48) = 2.70$, $p = .11$, nor was the condition by group interaction, $F < 1$.

A 2 X 2 ANOVA on the uncorrected data ($n = 37$) showed a significant main effect of condition, $F(1, 35) = 24.75$, $MSE = .19$, $\eta_p^2 = .41$, $p < .001$. Interestingly, the analysis also revealed a significant main effect of group, $F(1, 35) = 4.51$, $MSE = .28$, $\eta_p^2 = .11$, $p < .05$, with RGs ($M = .62$, $SEM = .04$) more conservative than the NGs ($M = .73$, $SEM = .04$). This main effect was qualified by a significant interaction between group and condition, $F(1, 35) = 9.85$, $MSE = .19$, $\eta_p^2 = .22$, $p = .003$. The interaction may have occurred because the RGs were more sensitive to the manipulation of difficulty compared to the NGs.

Considering the gambling criteria analyses on the corrected and uncorrected data, the correction that had been applied to the cells is called into question. Whilst the correction has been endorsed by several researchers (e.g., Hautus, 1995; Macmillan & Creelman, 2005), the adjustment may be interfering with the true frequencies. More specifically, it is a possibility that the main effect of group was not observed in the analysis on the corrected data because the correction of adding 0.5 to each frequency cell of Table 2.1 has altered the statistical bias and standard error (see Verde, Macmillan & Rotello, 2006, for a discussion regarding the transforming, discarding or replacing undefined HRs and FARS). Alternatively, it may be the case that there simply were not enough participants to reach a firm conclusion.

Other researchers have criticised the statistical measure of *c,* which is a measure of the distance between the criterion and the intersection point of the correct and incorrect distributions, as this measure does not specify the location of the intersection (Bruno & Rutherford, 2010). Hence, if the intersection shifts, the value of *c* would change and could suggest that the criterion has shifted which may not be the case (see also Stretch & Wixted, 1998). Therefore, FARs were analysed which is a purer and more objective measure of criterion shifts. FARs are not contaminated by accuracy/resolution differences, as it is assumed that the incorrect distribution does not move (see the introduction of Experiment 6 in Chapter 5 for a full discussion of the reasoning behind FAR analysis). Also, the FARs for every participant are included in the analysis, leaving behind the possibility of corrections interfering with the results. Thus, the 2 X 2 mixed ANOVA on the FARs revealed no main effect of condition or an interaction, both *Fs* < 1. The main effect of group was approaching significance, $F(1, 48) = 2.95$, $MSE = .18$, $\eta_p^2 = .06$, $p = .09$, with fewer FAs committed by the RGs (*M* = .42, *SEM* = .06) compared to the NGs (*M* = .57, *SEM* = .06). This finding demonstrates a trend that supports the expertise-transference hypothesis as the RGs are more sensitive than the NGs when setting their criteria; the RGs are more reluctant to use the gamble option when the 0/3 decision is incorrect.

Individual Sum Plots and Optimality

To further investigate the gambling control set by the two groups, individual sum plots were plotted for each individual sum. The gambling likelihood (GL, the tendency to gamble, see Table 1.2 for the calculation of this measure) was plotted alongside the optimal gambling likelihood (OGL or optimal bias, see Appendix A for the methodology behind this measure) for each group for the easy (Figure 3.6) and difficult (Figure 3.7) conditions. Figures 3.6 and 3.7 are remarkably similar, but this is not surprising given that all that is differing between them is the *frequency* of trials for each sum. Participants in both groups were responding too liberally across the middle sums between 6 and 11, which prevented them from optimising their scores based on the set reward and penalty.

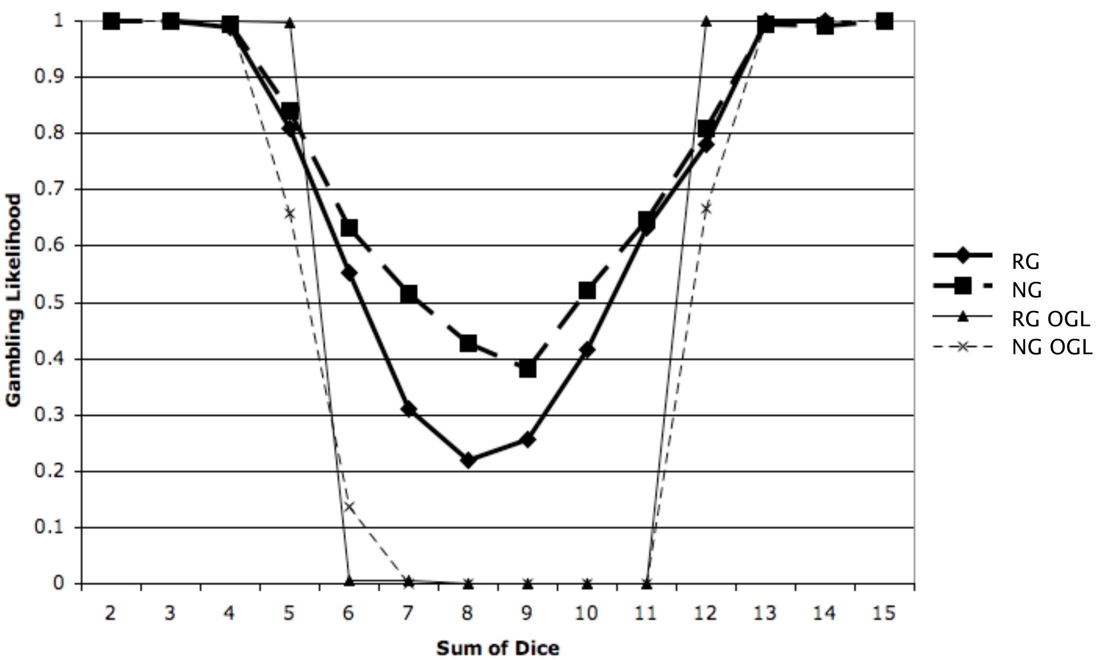

Figure 3.6. The sum plot of both groups in the ‘easy’ condition of Experiment 3. RG = regular gamblers; NG = non-gamblers; OCS = optimal gambling likelihood.

As the FAR analysis indicated a significant main effect of group, it was decided that a 2 (group: RG, NG) X 2 (condition: easy, difficult) mixed ANOVA was conducted on absolute deviation from optimal bias across all sums. Group was the only between-participant variable. We wanted to further explore how the RGs and NGs differed in their gambling, and whether the RGs' lower FAR was more optimal for the demands of the task (difficulty manipulation and rewards and penalties) than the NGs' FAR (see Table 1.2 for the formula and Table 3.8 for the means and SEs). No gambling criteria differences were detected between the two groups in Experiments 1 and 2 so this deviation analysis was not conducted previously.

The analysis indicated that across all sums, there was no statistical difference between the groups in terms of how optimal they were setting their gambling criterion, as neither the main effect of group or the condition by group interaction was significant, largest $F(1, 48) = 2.78$, $p = .10$. This finding may be a result of the RGs experiencing fewer deterministic sums, for example, in the difficult condition the RGs were required to gamble on sums between 4 and 13, but the NGs gambled on sums between 3 and 14.

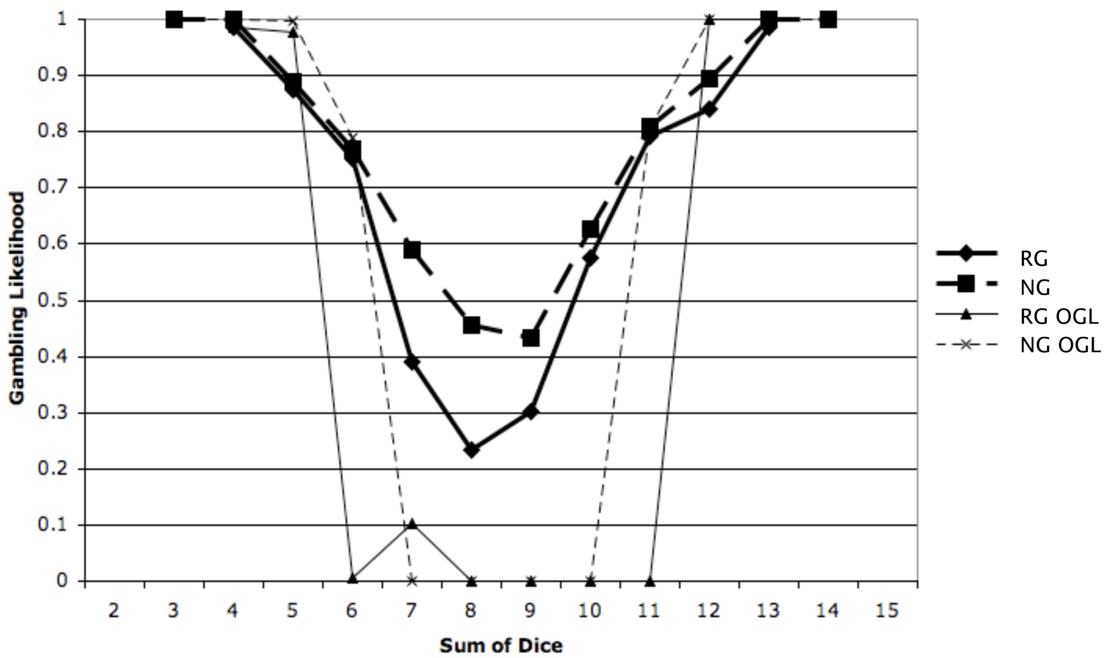

Figure 3.7. The sum plot of both groups in the 'difficult' condition of Experiment 3. RG = regular gamblers; NG = non-gamblers; OGL = optimal gambling likelihood.

Participants were, however, closer to their optimal criterion in the easy condition (deviation M = .14, SEM = .01) compared to the difficult condition (deviation M = .31, SEM = .03). In contrast to ambiguous sums, in deterministic sums the identity of the unique die is a clear right or wrong answer, so it is easier for the participants to perform close to optimal as the answer is the same each trial. For instance, the unique die always has to land on a 0 when the sum of 4 is presented.

However, both sum plots clearly demonstrate that the RGs are more conservative than the NGs between the more probabilistic sums of 5 and 12. To determine statistically how optimally each group was gambling for the sums of 5 to 12, another 2 (condition) X 2 (group) mixed ANOVA on absolute deviation from optimal gambling was conducted. This ANOVA revealed a significant main effect of group, $F(1, 48) = 6.02$, $MSE = .16$, $\eta_p^2 = .11$, $p = .02$. The RGs (M = .41, SEM = .06) were gambling closer than the NGs (M = .61, SEM = .06) to how they should optimally be gambling. The main effect of condition and the condition by group interaction were not significant, both $Fs < 1$.

Table 3.8.

The Overall Accuracy for each Sum Presented to Participants in each Condition of Experiment 3.

	Sum of Dice													
Group	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	Easy Condition													
RG		.99	1	.79	.64	.56	.43	.47	.60	.66	.79	1	.99	
NG	1	1	1	.73	.60	.58	.51	.43	.61	.60	.73	.99	.99	1
	Difficult Condition													
RG			.99	.82	.65	.58	.51	.52	.65	.66	.81	1		
NG		1	1	.77	.74	.58	.49	.51	.65	.72	.78	1	1	

Note: In order to manipulate difficulty whilst equating accuracy, both groups were presented with slightly different sums with varied frequency of presentation, hence the empty cells in the table above (see Table 3.4 for the frequencies of sums presented to each group). RG = regular gamblers; NG = non-gamblers.

From the analyses, we can conclude that whilst the RGs and NGs appear to be gambling similarly when taking into account all sums (as indicated by the gambling criterion analyses and the deviation from optimal gambling likelihood analyses). However, based on the data, the RGs are performing closer to optimality between the ambiguous sums of 5 and 12 when there is a greater chance element to the dice task (see Table 3.8 for the overall accuracy achieved by each group for each individual sum in the easy and difficult conditions).

Summary

In summary, Experiment 3 manipulated difficulty of the dice task by varying the frequency of deterministic (sums with definitive right or wrong decisions, 2-4 and 13-15) versus ambiguous (sums with probabilistic decisions, 5-12) sums. The most important finding of Experiment 3 was that RGs were more sensitive than NGs to the sum difficulty and set a criterion closer to optimal for the ambiguous sums. NGs also gambled less often on ambiguous sums compared to extreme sums, but their sensitivity to the nature of the sum was less than that of RGs, and their criterion setting was further from optimal. One possible explanation for this variance is that the more experienced players encounter probabilistic and chance outcomes in real life gambling. It is conceivable that this experience provides the main justification why RGs' gambling performance excels over the NGs. Perhaps by setting more optimal criteria, the RGs showed greater enhancement of gambled accuracy versus overall accuracy compared to NGs. These results support the expertise-transference hypothesis; that is, the finding suggest that regular gambling leads to the development of enhanced betting control in relation to the more probabilistic outcomes, which the RGs are able to transfer to the novel dice task.

There were no differences between the RGs and NGs in terms of either accuracy or resolution. Of course, the groups were equated on accuracy using pilot data, so the accuracy result was expected. No attempt was made to equate the groups on resolution, and no group differences were observed whether it was indexed by gambling decisions or subjective confidence; however, had resolution differences been found, they may have be difficult to interpret given that slightly different frequencies of sums were presented to each group. By far, the largest determinant of resolution related to the individual sums themselves, with better resolution for definitive, easy sums. With these sums, correct 0/3 decisions were straightforward, and participants would know that these decisions were correct. Indeed, resolution in this task is largely down to chance in that there is very little that can be done to improve it over trials.

Discussion of Chapters 2 & 3

The experiments in Chapters 2 and 3 were conducted with two main objectives in mind: the first was to find an appropriate gambling task that would work well with the SDT framework to elucidate cognitive and metacognitive differences of participants. The second objective was to investigate how regular gamblers differed in their decision-making from non-gamblers when presented with different manipulations of bias. In relation to these experiments, it is hypothesised that learning more about how regular gambling exposure impacts on individuals' decision-making may give us insight into why a minority of individuals develop problems with gambling.

Overall, the experiments reported in Chapters 2 and 3 illustrated mixed findings. Experiment 1 (penalty manipulation in blackjack task) demonstrated that the RGs had better resolution than the NGs but group differences in resolution were not found in either of the other experiments. It appears that practice with gambling tasks, and in particular, prior experience with blackjack, contributed to the RGs' better discrimination between their correct and incorrect decisions.

While findings did not indicate differences between the RGs and NGs in Experiment 2, which manipulated rewards in a novel dice task, the individual sum plots demonstrated that the RGs appeared to be setting a more optimal gambling criterion on the most probabilistic sums of the low-reward condition. In light of the chance component of gambling games, we may need to concede the difficulty of transferring the RGs' gambling experience or capacity to new gambling tasks. This limitation has also been found in other studies. For instance, Cantinotti, Ladouceur and Jacques (2004) assessed the extent to which expert hockey bettors could make better predictions than chance during a hockey league season. The findings showed that expert bettors could make more accurate predictions than amateur bettors, but these predictions did not result in a higher payout than chance. The researchers suggested that the expertise of gamblers is related to cognitive distortions than actual skill. Chance appears to have too great an influence on some games for experienced bettors to perform 'expertly', which leads gamblers to believe that they have a higher probability of winning and overconfidence (see also Ladouceur, Giroux and Jacques, 1998). Importantly, none of the participants in Cantinotti et al.'s (2004) research were problem gamblers, as screened using the SOGS. Delfabbro and Winefield (1999) argued that the feelings of overconfidence result from gamblers not assessing their own accuracy appropriately, including ‘near-misses’ as successes, which creates cognitive biases and illusions of control.

Similarly, Wagenaar and Keren (1985) explored how well statistical experts, professional dealers and control group participants were calibrated when they assessed the probability of card combinations in real-life blackjack. The researchers found that expertise and statistical expertise did not lead to better calibration.

In contrast, Ceci and Liker (1986) found that expert horse race bettors learnt a very complex decision-making process through their experience and could more successfully predict the ‘top horse’ at race time according to the betting public, and the ‘top three horses’ in their exact order of odds at race time compared to non-experts. Experts demonstrated a complex interactive reasoning process whereby as many as seven variables (e.g., last race speed, track size, race conditions) which were both additive and interactive, contributed to overall handicapping scores. In an observation that may resonate within the present research, the researchers argued that distinctions between expert gambling literatures relate to researchers’ classification of ‘experts’ and the individuals’ goals (e.g., playing for excitement and longevity of a game versus playing for money). In addition, Ceci and Liker (1986) demonstrated that IQ was not correlated with expertise in horse race betting.

In support of Ceci and Liker’s findings on the development of expertise in gambling tasks, Experiment 3 (difficulty manipulation in the novel dice task) found that the RGs could strategically regulate their accuracy more effectively than the NGs by using the gamble option. RGs were also more sensitive to the underlying dice probabilities compared to the NGs, which was shown by a more optimal gambling strategy used when presented with ambiguous sums.

This lack of consistency of the experimental findings discussed in this chapter needs to be addressed before any firm conclusions can be drawn; however the findings so far are potentially very interesting. Resolution differences between the groups were observed in a task that the RGs were familiar with and may have had prior experience, but resolution differences could not be transferred to a novel task. However, bias sensitivity generalises to novel gambling tasks.

The experiments reported in this chapter have some limitations, which I will attempt to address in the future studies of this thesis to further investigate the expertise-transference hypothesis. First, the blackjack task of Experiment 1 was too simplistic with very high accuracy rates obtained by both the RGs and NGs. I was left with two choices: to continue with the blackjack task by adjusting it to make it more ecologically valid and increasing its difficulty, or to develop a different task that would lend itself to more strategic game play with clearer correct versus incorrect answers. In considering the focus of the studies and the possible explanations for differences observed between the RGs and NGs, it was decided that a novel task would be more suitable than a task that many participants (both regular and non-gamblers) knew how to play. A novel task would eliminate prior practice and knowledge variables that are difficult to control and would allow us to concentrate on the transference of expertise hypothesis, and subsequently conclude as to whether expertise can develop in gambling contexts.

Secondly, as I now have a better idea of how participants are gambling to the trials, I can ensure that the wager parameters are appropriately set in future experiments. It was proposed that the reward manipulation payout structures of Experiment 2 were too similar to each other to detect a difference in gambling control between the two groups. In advance of further studies, the payout structures can be manipulated using hypothetical bias profiles so that the payouts are extreme enough to allow criterion shifts between conditions.

Thirdly, in relation to Experiment 3, the experimental (RGs) and control (NGs) participants should ideally have identical stimuli, which was not the case with the manipulation of difficulty. The reasoning behind the equation of accuracy was so that we could focus solely on the gambling control measure. However, it was found that the manipulation of difficulty impacts on both resolution and accuracy. Therefore, future manipulations of bias exploring group differences should likely be conducted on the manipulation of rewards and penalties, rather than difficulty.

In summary, type-2 SDT was used successfully to separate important cognitive and metacognitive variables of decision-making in three gambling experiments discussed in this chapter. SDT analysis had previously not been used to explore the decision-making differences between groups of gamblers and non-gamblers. An important conclusion that arose from the findings was that the dice task is a suitable experimental task, not only to assist in our understanding of the cognitive and metacognitive processes underlying gambling behaviour, but also to enhance our knowledge of the optimality of individual decision-making in a gambling context - a key measure of the current research. The expertise-transference hypothesis maintains that RGs, as a result of experience, learn the impact of criterion setting on gambling success and are therefore more responsive to bias manipulations and perform more optimally than NGs in new tasks. While some significant findings were shown, more investigations need to be pursued in order to support the expertise-transference hypothesis. This transference would provide evidence to support that the expertise that develops with regular gambling is a complex informational process rather than over learned, rote repetition (Ceci & Liker, 1986). Fully understanding this phenomenon in gambling demands new, perhaps unconventional, ways of approaching the expertise-transference hypothesis.

The following chapter outlines another reward manipulation in the dice task (Experiment 4) with different wager parameters than the ones chosen in the present chapter, and a manipulation of penalties (Experiment 5), as support for the expertise-transference hypothesis. The Chapter 4 was published in The Quarterly Journal of Experimental Psychology in September 2011, co-written with my supervisor, Dr Philip Higham.

CHAPTER 4

EXPERTISE AND GAMBLING: USING TYPE-2 SIGNAL DETECTION THEORY TO INVESTIGATE DIFFERENCES BETWEEN REGULAR GAMBLERS AND NON-GAMBLERS[12]

Gambling has been seen historically as a form of deviant behaviour, often associated with organized crime, antisocial acts, comorbidity with substance abuse, alcoholism and other addictive behaviours (Breen et al., 2001), particularly amongst the working classes (Downs, 2008). Views on gambling in the UK have become increasingly relaxed due to more liberalised government legislation. For instance, the introduction of the National Lottery in the UK in the 1990s made a significant impact on social attitudes towards gambling, making gambling for money an increasingly popular and socially acceptable activity (Rogers, 1999), to the point that approximately 68 percent of the UK population participate in some form of gambling activity each year (48 percent excluding the National Lottery; Wardle et al., British Gambling Prevalence Survey, 2007). There has also been a substantial increase of remote gambling opportunities in terms of Internet, television and mobile gambling (Griffiths, 1996, 2007). [13]

Signal Detection Theory and Gambling

Regardless of whether individuals are gambling for the first time or not, one aspect they are able to control in a gambling situation is their *criterion setting*. Criterion setting in this context refers to gamblers' willingness to gamble (potentially gaining points or money, but risking loss) versus pass (in which case no gains or losses are garnered). Individuals who perform well on gambling tasks (e.g., professional poker players) will generally set a criterion that is close to optimal, gambling on the outcomes that are most likely to earn them rewards, and choosing to skip a round or walk away when the chances of winning are against them. In contrast, poor performance on gambling tasks may be attributable to an overly liberal criterion (gambling too often) that may lead to *sunk costs* (e.g., Goodie, 2005). Alternatively, a

[12] Published by Lueddeke & Higham (2011), *Quarterly Journal of Experimental Psychology, 64(9),* 1850-1871.
[13] Some parts of the introduction of this paper originated from the introductory chapter of this thesis.

criterion that is too conservative may also be detrimental in that gamblers will lose out on winnings they may otherwise have obtained (*opportunity cost*). Criterion setting is, therefore, a pivotal challenge for all types of gamblers in that it partially determines the success or failure they will experience in gambling settings in which a pass option is available. Furthermore, research focused on ascertaining the optimal criterion setting (or optimal bias), and how gamblers perform with respect to it, is important to understanding gambling behaviour, whether that behaviour be problematic or not.

One tool we can use for investigating both actual and optimal criterion setting in a gambling domain is Signal Detection Theory (SDT). Typical applications utilise *type-1* SDT which provides researchers with the tools to analyse data from cases in which observers are required to distinguish between stimuli that are generated from a known process (*signal*) versus generated by chance (*noise*). For example, a common application of SDT has been medical diagnosis (e.g., Fryback & Thornbury, 1991; Getty, et al., 1988; Lusted, 1971). Two parameters are usually derived from SDT: an individual's ability to discriminate between the signal and noise, and the response criterion that the individual sets (Abdi, 2010; Green & Swets, 1966; MacMillan & Creelman, 2005).

A lesser-known version of SDT, known as *type-2,* requires observers to discriminate between their own correct versus incorrect responses, and it is this type of SDT that is most relevant to gambling.[14] For example, in many gambling scenarios, the gambler must make some kind of decision, assess its accuracy, and then decide whether or not to gamble based on the outcome of that assessment. Because self-assessment is involved in this type of gambling decision, type-2 discrimination is inherently metacognitive, which differentiates it from type-1 SDT in which discrimination is a measure of bias-free accuracy (for discussion see Higham, 2002, 2007). In the metacognitive literature, the ability to discriminate between accurate and inaccurate responses is known as *resolution* (e.g., Koriat & Goldsmith, 1996; Higham, 2011).

Although most work on SDT has been type-1 (e.g., Erev, Bornstein, &

[14] Type-1 SDT may have some application to gambling in that some games such as poker involve the detection of deception in other players. However, in many other games, the decision to gamble or pass involves assessing whether a candidate response is correct (which will be rewarded if gambled) or incorrect (which will be penalized if gambled). It is this latter type of discrimination that is the focus of this paper.

Wallsten, 1993; Gordon-Salant, 1985; Green & Swets, 1966; Lockhart, 2000), recently some research has applied type-2 SDT to post-decision wagering (e.g., Dienes & Seth, 2010; Fleming & Dolan, 2010; Koch & Preuschoff, 2007; Persaud, McLeod & Cowey, 2007, 2008). For instance, Persaud et al. (2007) demonstrated in an implicit learning study, which required participants to wager 'high' or 'low' on grammaticality decisions, that individuals failed to maximize cash earnings by wagering 'high' on supposedly 'unknown' decisions that had above chance accuracy. The wagering and type-2 discrimination literature has mostly centred on issues surrounding measures of awareness (see also Clifford, Arabzedah & Harris, 2008; Dienes & Seth, 2010; Fleming & Dolan, 2010), rather than appropriate placement of wagering criterion. Hence, given the importance of criterion placement in determining gambling outcomes and understanding gambling behaviour, there is a need for research exploring type-2 gambling decisions and the role that expertise plays in optimising bias.

Optimal Criterion Setting

Using SDT, it is possible to construct a theoretical model to determine how an ideal observer (IO) would perform given the payoffs in a particular context (Wickens, 2002). If an observer has set an optimal criterion, then rewards will be maximised and penalties will be minimised, by varying the criterion according to different situations. The maximum payout that is obtainable is not just based on criterion setting, but also on the IO's discrimination (which may not be optimal), the prior probability of a signal (i.e., the base-rate probability), and the payoff matrix. However, given a certain level of discrimination, the prior probabilities, and payoffs, the IO adopts an optimal criterion that is best for the given situation. The IO's performance can then be compared to the performance of the actual observer to establish how optimally – or non-optimally– the actual observer is performing.

Optimal observer research has focused on *type-1* discriminations and suggests that individuals' criterion setting is typically suboptimal (Fisher, 1986; Green & Swets, 1966; Maddox & Dodd, 2001; Peterson & Beach, 1967), particularly when payoffs for correct versus incorrect responses are unequal (Maddox, 2002). Suboptimal criterion placement may be a result of a slow learning process (Erev, 1998) associated with lack of experience on task characteristics such as level of difficulty and monetary gains (Ulehla, 1966). One possibility is that experts in a domain-specific task may learn through practice to set a more optimal decision criterion compared to novices. Indeed, recent research on expertise suggests that this is the case; experts have been shown to set a response criterion that results in them having better performance than novices on a variety of tasks including disease detection (Parasuraman, 1985), deception detection (Cañal-Bruland & Schmidt, 2009; Meissner & Kassin, 2002), and air-traffic control (Bisseret, 1981).

Over the last few years, Higham and colleagues (e.g., Higham, in press, 2002, 2007; Higham & Arnold, 2007a, 2007b, Higham & Gerrard, 2005; Higham, Luna, & Bloomfield, 2010; Higham, Perfect, & Bruno, 2009; Higham & Tam, 2005, 2006) have utilised type-2 SDT to separate the underlying cognitive and metacognitive components of performance on a variety of tasks ranging from cued recall to multiple-choice testing. Higham (2007) and Higham and Arnold (2007a, 2007b) developed a methodology based on SDT that estimates the optimal setting of the type-2 criterion on formula-scored educational tests for which errors are penalised.[15] This methodology also allows one to estimate the maximum score that individuals would achieve if they employed that optimal setting. To our knowledge, theirs is the only research to consider optimal criteria in a type-2 SDT context, and their analytic tools will be adopted in this study (see Appendix A for computation of optimal bias and maximum score).

Study Overview

The primary aim of our experiments is to examine optimal criterion setting in a gambling domain using Higham's (2007; Higham & Arnold, 2007a, 2007b) unique methodology within a type-2 SDT framework. Our main interest is to investigate the criterion placement, and the possibility of differential sensitivity to bias manipulations, of regular non-problem gamblers (RGs) and non-gamblers (NGs)

[15] Higham's (2007) method for estimating optimal criterion setting was designed for formula-scored tests that are written by students in educational settings. There are no doubt some important differences between performance on formula-scored tests and performance on a dice game. However, in terms of the soundness of the methodology, the similarities are more important than the differences. For example, formula-scored tests incorporate a point system just like the current gambling task; points are added if an answer is correct but taken away if the answer is incorrect, but these points only apply if an answer is offered (gambled). No points are won or lost if an answer is withheld (guessed). Thus, just as with the dice game, it is possible to calculate overall accuracy, resolution (type-2 discrimination) and bias. We refer interested readers to Higham (2007) and Higham and Arnold (2007a, 2007b) for details regarding the logic, assumptions, and computations that are necessary to generate these estimates.

when making decisions under uncertainty.

On the one hand, presenting regular gamblers with a novel gambling task may produce poor betting control with less than optimal gambling criteria and insensitivity to bias manipulations, similar to what is expected for the NGs. This is due to the RGs having no previous experience on the particular game in question and we refer to it as the *specificity hypothesis*. On the other hand, RGs may transfer their learned gambling skills to novel tasks quite readily such that their performance is closer to optimal compared to the NGs. We refer to this as the *expertise-transference hypothesis*.

We outline two experiments to test these hypotheses and explore the influence of expertise in optimal criterion setting using a type-2 signal detection framework, which to our knowledge has not been addressed in previous literature. In Experiment 4, we manipulated bias by manipulating rewards for type-2 hits (Hs), with the hypothesis that a high-reward task will result in a more liberal criterion setting than a low-reward task. In Experiment 5, criterion setting was manipulated by varying penalties for type-2 false alarms (FAs).

Experiment 4

Method

Participants. Thirty RGs and 29 NGs (students and staff of the university) aged between 18 and 38 years (M = 23.22, SD = 6.08) volunteered to participate in the experiment after reading an advertisement on the University of Southampton's campus (see Table 4.1 for the specific demographics of each group). RGs were classified as individuals who gambled at least once a month on any gambling activities that involved money, such as going to casinos, betting shops, bingo, gaming venues or playing online or with friends. All RGs gambled regularly on *at least* two forms of gambling activities (i.e., poker and betting), and the vast majority of RGs played games of both 'skill' (e.g., blackjack) and 'chance' (e.g., slot machines). Participants who scored three or above on the *South Oaks Gambling Screen* (SOGS; see Lesieur & Blume, 1993) were excluded from the study, as they were potentially problematic gamblers, and it was the difference between NG and (non-problem) RGs that was the main focus of our research. Individuals who *only* played the National Lottery were also excluded from the study. NGs were individuals who never gambled. The majority of participants completed the experiment in a research laboratory on campus, but the dice-game was also sent as a file attached to an email to approximately a third of each group (see Table 4.1) to gain access to a greater number of participants.

Table 4.1

Demographics of the Non-Gambler and Regular Gambler Groups of Experiments 4 and 5.

	Experiment 4		Experiment 5	
Demographics	NG	RG	NG	RG
Mean age (years)	23.07	22.90	21.31	23.54
SD	4.59	4.43	4.49	7.27
Males (%)	59	80	24	54
Ethnicity (%):				
Caucasian	59	77	83	93
Chinese	14	10	7	4
Asian	10	10	0	3
Mixed & Other	17	3	10	0
Educated to (%):				
School (16 years)	0	3	0	0
College (18 years)	10	17	17	14
Undergraduate	55	70	72	82
Postgraduate	35	10	11	4
Completed task at home (%)	28	30	3	11
SOGs score	0	1.63	0	2.21
HADs:				
Anxiety score, *M (SD)*	3.03 (2.56)	3.80 (3.29)	3.66 (2.42)	3.93 (2.83)
Depression score, *M (SD)*	1.34 (1.81)	1.90 (1.83)	1.72 (2.10)	2.39 (2.29)

Note: NG = non-gamblers; RG = regular gamblers; SOGS = South Oaks Gambling Screen; HADS = Hospital Anxiety and Depression Scale.

Participants were offered £6 as an incentive for completing the study. Additionally, an incentive of £20 worth of vouchers was offered to the highest scoring individual.

Design and Materials. The *Hospital Anxiety and Depression Scale (HADS, Zigmond & Snaith, 1983)* questionnaire containing 14 items (seven items on depression [HADS-D] and seven items on anxiety [HADS-A]), was used to determine whether participants presented with anxious or depressive symptoms, which could impact on their cognitive functioning and decision-making (e.g., De Visser et al., 2010). Each item is scored from 0 (minimally present) to 3 (maximally present), giving maximum scores of 21 for each subscale. A score of 11 or more on either subscale is considered to be diagnostic of either an anxiety or depressive disorder. Scores of 8-10 represents 'borderline' problems and scores of 0-7 are within the 'normal' range.

The *South Oaks Gambling Screen – Revised (SOGS;* Lesieur & Blume, 1993) was also administered to participants. The SOGS is a 16-item psychometrically validated measure of pathological gambling. Items reflect symptoms of pathological gambling. A criterion score of 5 or more has been validated for identifying pathological gamblers, and a score of 3 or 4 represents an individual who may have some gambling issues. Therefore, participants who gambled regularly (at least once a month) and scored less than 3 on the SOGS were included in the study. Although the SOGS has been primarily employed as a screening device to identify problem gamblers, the present study uses the SOGS as an index of gambling severity. Many studies have suggested that whilst most screening instruments have limitations, the SOGS is an appropriate measure in discriminating non-problem gamblers from problematic gamblers (Oliveira, Silva, da Silveira, 2002; Weinstock, Whelan, Meyers & McCausland, 2007).

A computerised gambling task, inspired by Green and Swets (1966), was designed to resemble an actual dice gambling game that may be played in a gaming venue or on the Internet, whilst keeping the task novel for both groups of participants. In this game, three dice are rolled 'virtually'. The first two dice are normal, yielding a value between 1 and 6. The third *anomalous die*, however, has 3 appearing on three faces and 0 appearing on the other three. On a given trial, the gambler sees only the sum of the three dice (between 2 and 15) and must indicate whether the 0 or the 3 was face-up on the anomalous die. Hence, if the displayed sum is 2, 3, or 4 on the one hand versus 13, 14, or 15 on the other, the correct responses are necessarily 0 versus 3, respectively. No other values of the anomalous die would be possible because the lowest sum for a 3 face on the anomalous die is 5 (1 + 1 + 3), whereas the highest sum for a 0 face is 12 (6 + 6 + 0). However, there is more uncertainty surrounding other sums. For example, a sum of 8 is 56 percent likely to have a 0 face on the anomalous die.

For each trial in each experiment, a computer algorithm sampled a sum with particular values of the three dice, the sum was presented to participants, and three decisions were required. First, participants chose either a '0' or '3' response. Second, they decided whether to *gamble* or *guess* their 0/3 decision. If they chose to gamble their 0/3 decision and it was correct, points were gained and added to their running total. However, if their 0/3 decision was gambled and it was incorrect, points were lost and deducted from the total.[16] If, instead, participants chose to guess, points were neither gained nor lost regardless of the accuracy of the 0/3 decision. The gamble versus guess decision is essentially akin to the bet versus fold decision needed in other games such as poker. Finally, a confidence rating was required. The purpose of the game was to maximise the total number of points over trials.

Shown in Table 2.1 is a 2 X 2 contingency table, which can be used to derive most of the measures that we will be using to analyse performance on the dice task. There are four possible contingencies shown in the table: a correct 0/3 decision that is gambled (hit, H), an incorrect 0/3 decision that is gambled (false alarm, FA), a correct 0/3 decision that is not gambled (i.e., guessed; miss [M]), and an incorrect 0/3 decision that is guessed (correct rejection [CR]). These four frequencies can be used to compute typical measures of gambling performance such as total score, which is dependent on the rewards and penalties associated with gambling, and overall accuracy, calculated on the basis of the 0/3 decision without regard for the gambling decision or the point system being used (see Table 1.2). Overall accuracy is represented in Table 2.1 by the column marginal frequencies.

The four frequencies also allow for the computation of a type of hit rate (HR) and false alarm rate (FAR), which, in turn, can be used to compute informative SDT performance measures that are not typically examined in gambling research and

[16] The number of points won or lost for a gamble decision varied between conditions as explained in detail below.

which allow us to examine gambling control. A type-2 SDT measure of *bias* (response criterion) can also be derived from the HR and FAR (see Table 1.2). In this dice-game context, bias refers to gamblers' tendency to gamble versus guess. In SDT, bias derives from a gambling criterion that is placed on a subjective dimension of confidence. If confidence in the accuracy of a given 0/3 decision is equal to or exceeds the gambling criterion, a decision to gamble is made. Otherwise, a guess decision is made. The gambling criterion is assumed to be malleable and controllable. For example, if the reward for Hs is high and the penalty for FAs is low, participants will tend to set a liberal gambling criterion, choosing to gamble on most trials. Conversely, if the reward for Hs is low and the penalty for FAs is high, the criterion will be set more conservatively such that more confidence is needed in the accuracy of a 0/3 decision before a gamble decision is made. Bias is assumed to be statistically independent of both the overall accuracy of the 0/3 decision and discrimination, although in practise, correlations between these measures may be observed. In terms of Table 2.1, the row marginal frequencies are indicative of bias, although other measures such as the FAR can be used. Because the gambling criterion is under gamblers' control, bias is a critical component of performance given our current interests.

Procedure. The research protocol was reviewed and approved by the University of Southampton's Psychology Ethics Committee. The SOGS was emailed initially to all volunteers to determine their eligibility to participate. Individuals who qualified for the study (i.e., gambled on a regular basis without indicating problematic gambling, or did not gamble at all) were assigned to one of the two experimental conditions. The participants were then given or sent (if they were participating over email) an informed-consent form along with questionnaires asking demographic details, and the HADS.

Experiment 4 manipulated rewards for Hs across two conditions of the dice task. In both conditions, participants lost 3 points for a FA, with the low- and high-reward conditions consisting of 1- and 2-point winnings for Hs, respectively. No points were assigned to either CRs or Ms. Selection of these particular parameters was based on pilot data indicating that optimal bias was likely to vary considerably between the experimental conditions if they were used.

The computer-based task was administered in a counterbalanced order with half of the participants in each group participating in the low-reward condition followed by the high-reward condition, and the other half participating in the conditions in the reverse order. Each condition contained 144 experimental trials and the trials were presented in a single random order to all participants. To generate these trials, sums associated with all 72 (6 x 6 x 2) possible combinations of the three dice were presented to participants twice (72 x 2 = 144). This presentation method meant that participants viewed sums that corresponded to the throwing of fair dice (i.e., each face on each die had a one-sixth probability of contributing to the presented sum). Participants were tested individually and full instructions on how to run the program, the rules of the game, and what to do after completion of the task were given in writing. Participants were initially required to complete five practice trials to become accustomed to the task. These trials were similar to the actual task.

Once the first condition was completed, participants had a two-minute break and then began the trials for the alternative condition (another 144 trials). The trials were self-paced and an additional break of two minutes was incorporated half way through each set of trials (three breaks in total). Participants were given immediate feedback on their responses in the form of a ‘points’ box in the top right of the computer screen accompanied by either a ‘ding’ or ‘buzzer’ sound through headphones to indicate a correct or incorrect answer, respectively. Participants who took part at home were instructed to situate themselves in a quiet room with no people or audio distractions, and to turn up the sound on their computer so they could clearly hear the audio feedback.

We thought that playing for money might encourage gambling behaviour after participation in the task, which we wanted to avoid, so participants played for points instead. However, an incentive of £20 worth of vouchers was also offered to the individual who scored the highest number of points across both tasks, in order to encourage more realistic gambling behaviour. A debriefing statement revealing the main hypotheses of the experiment followed the gambling task. Information on where to seek help with gambling problems, if needed, was also supplied (although no participants were problem gamblers).

Results and Discussion

The majority of the participants had an undergraduate degree or higher. The RGs were asked their most preferred games on which to gamble (listing up to five), and 73 percent of the sample enjoyed playing poker; 69 percent sports/horse betting; 45 percent blackjack or other card games; 23 percent roulette or slot machines; and 4 percent other games, such as chess and mahjong. RGs obtained an average score of 1.63 on the SOGS. None of the participants indicated that they were depressed or anxious, as measured by the HADS (see Table 4.1 for the means); however, two NGs and four RGs indicated that they were borderline anxious.

Chi-square tests and t-tests were conducted to determine whether the groups differed on any of the demographic measures.[17] The groups did not significantly differ in terms of age, $t(57) = -.14$, $p > .05$, ethnicity, $\chi^2(1) = 2.20$, $p > .05$, educational attainment, $\chi^2(1) = .82$, $p > .05$, anxiety, $t(57) = 1.00$, $p > .05$, or depression, $t(57) = 1.15$, $p > .05$, scores. The RGs had a significantly higher SOGs score than the NGs, $t(57) = 9.12$, $p < .001$, as anticipated. Further, the gender difference was approaching significance, $\chi^2(1) = 3.18$, $p = .08$, with a greater number of males in the RG group.[18] There were no differences in the results between the data gathered in the lab versus by email attachment.

In the following analyses, a type-2 SDT framework was implemented to investigate the main components of group performance, which include accuracy, gambling likelihood (response criterion), optimal gambling likelihood, and deviation from optimal gambling. Analyses of group performances across individual sums were also included.

Total scores. Total scores were computed as in Table 1.2. The data (means and SEs) for each of the groups across the two conditions are reported in Table 4.2. A

[17] Before conducting the χ^2 tests, some cells were collapsed for ethnicity and educational attainment analyses as more than 25% of cells had an expected frequency of less than 5. Chi-squared tests were conducted on Group (RGs, NGs) X Ethnicity (Caucasian, Chinese, Asian, Mixed and Other) and Group (RGs, NGs) X Education (undergraduate, school, college, postgraduate).

[18] Due to the uneven number of males and females in each group, all measures in the paper (total score, accuracy, gambling likelihood) were analysed both with and without gender as a between-subjects variable. Gender did not produce any main effects or interactions, largest $F(1, 53) = 3.00$, $p = .09$, and all important effects were significant with and without gender included as a factor in the analysis. Given these results, we report the analyses without gender to simplify the analyses and conclusions.

2X 2 mixed ANOVA, with group (RGs, NGs) as the between-subjects variable and condition (low-reward, high-reward) as the within-subjects variable, on the total scores revealed a main effect of reward condition, $F(1, 57) = 428.36$, $MSE = 321.66$, $\eta_p^2 = .88$, $p < .001$. As expected, the scores were considerably higher in the high-reward condition ($M = 67.41$, $SEM = 3.36$) compared to the low-reward condition ($M = -0.94$, $SEM = 2.94$). A main effect of group, $F(1, 57) = 12.86$, $MSE = 851.18$, $\eta_p^2 = .18$, $p = .001$, indicated that overall, the RGs ($M = 42.87$, $SEM = 3.77$) obtained higher scores than the NGs ($M = 23.60$, $SEM = 3.83$). NGs struggled with the low-reward condition so much so that they completed the task with a negative mean score of -9.83 (compared to the RGs mean score of 7.60 in the same condition). The interaction between condition and group was not significant, $F < 1$.

Table 4.2

Means, and Ranges of the Total Scores for Regular Gamblers and Non-gamblers in the Two Reward Conditions of Experiment 4.

		Experimental Condition	
Group		Low-Reward Condition	High-Reward Condition
NG	*M*	-9.48 (4.47)	56.69 (4.72)
	Range	-69 – 25	-15 – 109
RG	*M*	7.60 (3.83)	78.13 (4.77)
	Range	-48 – 31	-44 – 105

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Accuracy. Accuracy across all trials (i.e., overall accuracy = *f*) and on gambled trials (gambled accuracy) was computed for each participant (see Table 1.2 for the formulas and Table 4.3 for the means and SEMs). A 2 X 2 X 2 mixed ANOVA was conducted, with group (RGs, NGs) as the between-subjects variable and condition (low-reward, high-reward) and accuracy type (overall, gambled) as the within-subjects variables. The ANOVA yielded a main effect of group, $F(1, 57) = 7.06$, $MSE = .01$, $\eta_p^2 = .11$, $p = .01$, with the RGs demonstrating significantly higher accuracy ($M = .74$, $SEM = .01$) than the NGs ($M = .71$, $SEM = .01$).

Table 4.3

Mean Overall Accuracy and Gambled Accuracy as a Function of Group and Reward Condition in Experiment 4.

Group	Measure: Overall Accuracy	Gambled Accuracy
	Low-Reward Condition	
NG	0.67 (.01)	0.75 (.01)
RG	0.69 (.01)	0.80 (.01)
	High-Reward Condition	
NG	0.68 (.01)	0.75 (.02)
RG	0.70 (.01)	0.77 (.02)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

The main effect of accuracy type was also significant, $F(1, 57) = 75.20$, $MSE = .01$, $\eta_p^2 = .57$, $p < .001$. Gambled accuracy ($M = .77$, $SEM = .01$) was significantly better than overall accuracy ($M = .69$, $SEM = .00$). This finding shows that individuals were gambling on sums for which the 0/3 decision was most accurate, suggesting that participants as a whole were able to strategically enhance their accuracy using the gamble option. There was no main effect of condition, $F < 1$, which was anticipated as the same set of sums were presented to participants in each condition. However, there was a significant interaction between accuracy type and condition, $F(1, 57) = 5.46$, $MSE < .01$, $\eta_p^2 = .09$, $p = .023$. The difference between gambled accuracy ($M = .77$, $SEM = .01$) and overall accuracy ($M = .68$, $SEM = .01$) in the low-reward condition was greater than the same difference in the high-reward condition ($M = .76$, $SEM = .01$ versus $M = .69$, $SEM = .01$, for gambled versus overall accuracy, respectively). This finding suggests that the low-reward condition was associated with a more conservative gambling criterion than the high-reward condition; as long as participants have above-chance discrimination between their own correct and incorrect responses, then the difference between gambled accuracy and overall accuracy will increase as the criterion is made more strict (Higham, 2007;

Koriat & Goldsmith, 1996). No other main effect or interaction was significant from this analysis, largest $F(1,57) = 3.36$, $MSE < .001$, $\eta_p^2 = .06$, $p > .05$.

Table 4.4

Mean Gambling Likelihood, Optimal Likelihood and Deviation as a Function of Group and Reward Condition in Experiment 4.

	Measure		
Group	Gambling Likelihood	Optimal Likelihood	Deviation[a]
	Low-Reward Condition		
NG	0.68 (.04)	0.25 (.03)	-0.42 (.06)
RG	0.57 (.04)	0.37 (.03)	-0.21 (.06)
	High-Reward Condition		
NG	0.70 (.04)	0.81 (.03)	0.11 (.05)
RG	0.68 (.04)	0.80 (.03)	0.12 (.05)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

[a]This deviation measure corresponds to the deviation between the groups' optimal gambling likelihoods and their actual gambling likelihoods.

Actual versus optimal gambling likelihoods.[19] We turn now to the main research questions: how do RGs and NGs compare both in terms of their sensitivity to

[19] Gambling likelihood was chosen as a measure of bias because of its intuitiveness; a person who gambles a lot versus a little likely has a liberal versus a conservative gambling criterion, respectively. However, gambling likelihood can also be affected by variation in other performance parameters such as accuracy, so it is not a pure measure of bias. To ensure that the observed effects on gambling likelihood were indeed attributable to differences in criterion setting, we ran analogous analyses on the FARs. With such an analysis, liberal criterion setting is associated with a greater FAR than conservative criterion setting, and high sensitivity to our bias manipulations would be indicated by large changes in the FARs. Importantly, the 2 (group: RG, NG) X 2 (condition: liberal, conservative) X 2 (Experiment: 1, 2) mixed-model ANOVA on FARs yielded a significant Group X Condition interaction, $F(1, 112) = 5.54$, $MSE = .05$, $n_p^2 = .05$, $p = .02$, supporting the groups' differential sensitivity to bias manipulations demonstrated by the gambling likelihood analysis. The difference between the FARs in the liberal (high-reward and low-penalty) versus conservative (low-reward and high-penalty) conditions was much greater for the RGs (liberal $M = .64$, $SEM = .04$; conservative $M = .43$, $SEM = .04$) than the NGs (liberal $M = .65$, $SEM = .04$; conservative: $M = .58$, $SEM = .04$). The analysis further yielded a main effect of condition, $F(1, 112) =$

the bias manipulation and in terms of the optimality of their gambling criterion setting? To answer these questions, the optimal gambling likelihood (or optimal bias) was calculated for each participant using Higham's (2007) methodology. Computational details are shown in Appendix A.

Deviation from optimal bias was calculated for each participant (optimal gambling likelihood minus actual gambling likelihood). The actual and optimal gambling likelihoods, as well as deviation scores, are shown in Table 4.4. A 2 (group: RGs, NGs) X 2 (condition: high reward, low reward) X 2 (bias type: optimal, actual) mixed ANOVA conducted on the gambling likelihood data revealed main effects of condition, $F(1, 57) = 224.28$, $MSE = .02$, $n_p^2 = .80$, $p <.001$ and bias type, $F(1, 57) = 8.89$, $MSE = .06$, $n_p^2 = .14$, $p = .004$. As expected, both groups were more likely to gamble (i.e., more liberal bias) in the high-reward ($M = .75$, $SEM = .02$) compared to the low-reward condition ($M = .47$, $SEM = .01$), and their actual gambling rate ($M = .66$, $SEM = .03$) exceeded the optimal rate ($M = .56$, $SEM = .01$). The interaction between bias type and condition was also significant, $F(1, 57) = 119.33$, $MSE = .02$, $n_p^2 = .68$, $p <.001$. This interaction was caused by optimal bias being affected much more by reward condition than actual bias. Most critical, however, the three-way interaction was also significant, $F(1, 57) = 6.56$, $MSE = .02$, $n_p^2 = .10$, $p = .013$. This interaction reflected the fact that RGs tracked reward-based changes in optimal bias better than NGs. That is, although both groups deviated substantially from optimal criterion setting, and although neither group adjusted their criterion as much as they should have as rewards were manipulated, these problems were less for RGs than NGs. No other main effect or interaction was significant from this analysis, although the bias type by group interaction was marginal, $F(1,57)= 3.02$, $MSE = .06$, $n_p^2 = .05$, $p = .09$.

22.77, $MSE = .05$, $n_p^2 = .17$, $p < .001$. No other effects or interactions were significant, although the Condition X Experiment interaction was approaching significance, largest $F(1, 112) = 3.59$, $MSE = .19$, $n_p^2 = .03$, $p = .06$. Thus, the bias effects we observed on gambling likelihood are most likely attributable to movement of the type-2 gambling criterion and not due to differences in other parameters such as accuracy.

Low Reward High Reward

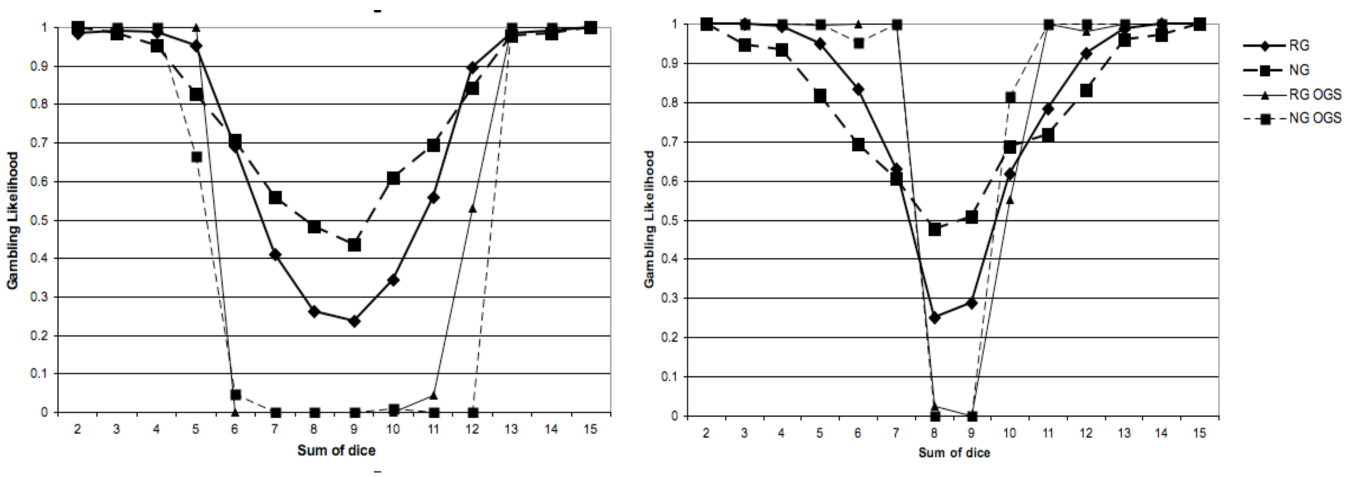

Figure 4.1. The sum plots of both groups in the low-reward and high-reward conditions of Experiment 4. RG = regular gamblers; NG = non-gamblers; OGS = optimal gambling setting.

The pattern of results suggested by the previous analysis is shown clearly in Figure 4.1, in which both the actual and optimal gambling likelihoods are plotted together as a function of each individual sum (ranging from 2 to 15). To create Figure 4.1, the four frequencies of the contingency table shown in Table 2.1 were determined *per sum*. These frequencies for individual sums were then treated as separate groups of trials, allowing several actual gambling likelihoods, as well as optimal gambling likelihoods (determined from bias profiles), to be plotted per participant.

The left panel of Figure 4.1 illustrates that participants in both groups should have been gambling less than 5 percent of the time, and often not at all, across the middle sums between 6 and 11 in the low-reward condition. Gambling too liberally across these sums prevented both groups from optimising their scores based on the reward and penalty that was applied. The sum plot also demonstrates that the RGs were rightly more conservative than the NGs between the sums of 7 and 11, with their actual-gambling likelihoods being significantly closer to the optimal-gambling likelihoods. Comparing the RGs' and NGs' performances on other sums also reveals RG's closer proximity to optimal gambling likelihoods. For instance, there is just 5 percent and 15 percent deviation between the RGs actual and optimal gambling likelihoods on the sums of 5 and 12, respectively. By comparison, the NGs deviate by 36 percent and 84 percent on these two sums. RGs also tracked optimal bias across the sums much more effectively in the high-reward condition (right panel) compared the NGs, which meant that they also tracked the bias manipulation more effectively, gambling more liberally for sums 2-7 and 10-15, and gambling more conservatively on the sums of 8 and 9.

By comparing the left and right panels of Figure 4.1, it is possible to observe the greater sensitivity to the bias manipulation for RGs compared to NGs that was discussed above. The sum plots for the NGs were virtually identical between the two reward conditions, whereas greater sensitivity to the bias manipulation was observed with RGs.

Summary. Experiment 4 demonstrated that RGs tracked optimal bias more effectively than NGs, and as a result, they were more sensitive to the bias manipulation created by task rewards. This finding may be explained by their previous experience with gambling. However, the RGs had many different gambling activity backgrounds, and they were not previously trained on the dice task. Therefore, to show superior accuracy and criterion setting compared to the NGs, they must have transferred their expertise gained through regular gambling to our completely novel gambling task. Thus, the results of Experiment 4 give support to the expertise-transference hypothesis and deny the specificity hypothesis.

However, the NGs may have been insensitive to the manipulation of bias because they were distracted by the high penalty used in Experiment 4. That is, in both reward conditions in Experiment 4, the penalty exceeded the reward (high reward: +2 reward versus -3 penalty; low reward: +1 reward versus -3 penalty). Presumably, NGs had little to no experience with payoffs systems such as this and they may have underestimated the impact that the variation in rewards would have on their point total, focusing primarily on avoiding the high penalty.

To test this hypothesis, we kept the rewards constant in Experiment 5 (+1 for a H) and manipulated the penalty for FAs (-1 and -4 for the low- and high-penalty conditions, respectively). If NGs are distracted by high penalties and ignore small rewards, then they should be as sensitive, or even more sensitive, than RGs to the manipulation of penalty in this experiment than the RGs. If, instead, RGs' greater sensitivity to the reward manipulation in Experiment 4 derived from their transferring expertise to a new domain (as per the expertise-transference hypothesis), then they should demonstrate greater sensitivity than NGs to the manipulation of bias in this experiment, just as they did in Experiment 4.

Experiment 5

Method

Participants. Fifty-seven participants (28 RGs, 29 NGs) aged between 18 and 50 years (*M*= 23.52, *SD*= 6.61) were recruited in a manner similar as participants in the previous experiment (see Table 4.1 for demographics of each group). Participants received £6 in exchange for their participation. An incentive of £20 worth of vouchers was again offered to the highest scoring individual to encourage more realistic gambling behaviour.

Design and Materials. The HADS and SOGS were administered to participants prior to the gambling task. The gambling task was the same basic dice task as in Experiment 4, but penalties rather than rewards were manipulated in this experiment in the manner described above.

Procedure. Participants were tested individually and given the demographic questionnaires, SOGS and HADS to complete. Participants completed the two gambling task conditions (low-penalty, high-penalty) in a counterbalanced order with a two-minute break in-between the blocks and two-minute breaks within each block. The task lasted an hour with 288 trials per condition. Sums associated with all 72 (6 x 6 x 2) possible combinations of the three dice were presented to participants four times (72 x 4 = 288). Double the number of trials was presented to participants compared to Experiment 4 to give the experiment more power.

Results and Discussion

Eighty-four percent of the participants had an undergraduate degree or higher, with the remaining being educated up to college level (18 years). The RGs were asked their preferred form of gambling, and 32 percent of the sample enjoyed playing poker; 28 percent, lottery; 21 percent, sports betting; 9 percent, scratch cards; 7 percent, slot machines; and 3 percent, other gaming machines. Analysis of the scores on the SOGS indicated that the RGs obtained a mean score of 2.21. None of the participants indicated that they were depressed or anxious, as measured by the HADS; however, three NGs and three RGs demonstrated borderline anxiety scores, and one NG and two RGs demonstrated borderline depression scores.

Similar to Experiment 4, the groups did not significantly differ in terms of age, $t(55) = 1.40$, $p > .05$, ethnicity, Fisher's exact probability = .42, educational attainment, $\chi^2(1) = .29$, $p > .05$, and anxiety, $t(55) = .42$, $p > .05$, or depression, $t(55) = 1.15$, $p > .05$, scores. The RGs had a significantly higher SOGs score than the NGs, $t(55) = 13.01$, $p < .001$, and there were significantly more females in the NG's group, $\chi^2(1) = 5.21$, $p = .02$.

Total scores. The 2 (group: RGs, NGs) X 2 (condition: low-penalty, high-penalty) mixed ANOVA conducted on the total scores (see Table 4.5) revealed a main effect of condition, $F(1, 55) = 149.69$, $MSE = 4449.89$, $\eta_p^2 = .73$, $p < .001$. As expected, the total scores in the high-penalty condition ($M = -54.03$, $SEM = 12.13$) were significantly lower than those in the low-penalty condition ($M = 98.87$, $SEM = 3.03$). Both the RGs and NGs had great difficulty with the high-penalty condition, completing the task with negative mean scores (-28.75 and -79.31, respectively) by the completion of the task. The RGs ($M = 38.43$, $SEM = 8.92$) obtained higher scores than the NGs ($M = 6.41$, $SEM = 8.76$) as indicated by a main effect of group, $F(1, 55) = 6.56$, $MSE = 2227.60$, $\eta_p^2 = .11$, $p < .05$, although there was no significant interaction between condition and group, $F(1, 55) = 2.20$, $MSE = 8899.76$, $\eta_p^2 = .04$, $p > .05$.

Table 4.5

Means and Ranges of the Total Scores for Regular Gamblers and Non-gamblers in the Two Penalty Conditions of Experiment 5.

		Experimental Condition	
Group		Low-Penalty Condition	High-Penalty Condition
NG	*M*	92.14 (5.10)	-79.31 (17.72)
	Range	22.00 – 129.00	-274.00 – 48.00
RG	*M*	105.61 (3.17)	-28.75 (16.51)
	Range	72.00 – 139.00	-194.00 – 94.00

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

Accuracy. A 2 X 2 X 2 ANOVA, with group (RG, NG) as the between-subjects variable, and condition (low-, high-penalty) and accuracy type (overall, gambled) as the within-subjects variables, was conducted on the accuracy data (see Table 4.6). The analysis yielded a significant main effect of group, $F(1, 55) = 9.87$, $MSE < .01$, $\eta_p^2 = .15$, $p = .003$. RGs were more accurate ($M = .74$, $SEM = .01$) than the NGs ($M = .71$, $SEM = .01$) in their decisions. The main effect of condition was also significant, $F(1, 55) = 8.90$, $MSE < .01$, $\eta_p^2 = .14$, $p = .004$; higher accuracy was observed in the high-penalty condition ($M = .73$, $SEM = .01$) in comparison to the low-penalty condition ($M = .71$, $SEM = .01$). This result was unexpected but could be due to the high penalty causing participants to be more vigilant in their decision making, consequently reducing their errors.

The analysis further yielded a main effect of accuracy type, with higher gambled accuracy ($M = .76$, $SEM = .01$) than overall accuracy ($M = .68$, $SEM = .01$). There was also a significant interaction between condition and accuracy type, $F(1, 55) = 17.60$, $MSE < .01$, $\eta_p^2 = .24$, $p < .001$. This interaction occurred because, in the high-penalty condition, there was a larger advantage of gambled accuracy ($M = .79$, $SEM = .01$) versus overall accuracy ($M = .68$, $SEM = .01$) than in the low-penalty condition ($M = .74$, $SEM = .01$ versus $M = .68$, $SEM = .01$ for gambled versus overall accuracy, respectively). These results show that both groups were able to enhance accuracy by selecting correct responses to gamble, but that this enhancement was greater in the high- than the low-penalty condition. The greater increase in accuracy for gambled responses versus all responses in the high-penalty condition compared to the low-penalty condition is most likely due the fact that participants set a more conservative gambling criterion. This pattern of results is analogous to that obtained in Experiment 4. No other main effect or interaction was significant from this analysis, largest $F(1, 55) = 3.31$, $MSE < .01$, $\eta_p^2 = .06$, $p > .05$.

Table 4.6

Mean Overall Accuracy and Gambled Accuracy as a Function of Group and Penalty Condition in Experiment 5.

	Measure	
Group	Overall Accuracy	Gambled Accuracy
	Low-Penalty Condition	
NG	0.67 (.01)	0.73 (.01)
RG	0.70 (.00)	0.74 (.01)
	High-Penalty Condition	
NG	0.67 (.01)	0.76 (.02)
RG	0.69 (.01)	0.81 (.02)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers

Actual versus optimal gambling likelihoods. As in Experiment 4, a 2 (group: RGs, NGs) X 2 (condition: low-penalty, high-penalty) X 2 (bias type: actual, optimal) mixed ANOVA was conducted on the likelihood data. Both actual and optimal likelihoods, along with the deviation score, are shown in Table 4.7. The analysis yielded main effects of condition, $F(1, 55) = 395.48$, $MSE = .03$, $n_p^2 = .88$, $p < .001$, and bias type, $F(1, 55) = 16.25$, $MSE = .07$, $n_p^2 = .23$, $p < .001$. Participants gambled much more often in the low- ($M = .86$, $SEM = .02$) compared to the high-penalty condition ($M = .42$, $SEM = .01$), and the actual gambling rate ($M = .71$, $SEM = .03$) exceeded the optimal gambling rate ($M = .57$, $SEM = .01$). There was an interaction between condition and bias type, $F(1, 55) = 104.29$, $MSE = .04$, $n_p^2 = .66$, $p < .001$. As in Experiment 4, although participants adjusted their gambling criterion as the penalty was increased, they did not do so as much as they should have. Most critically, however, there was a three-way interaction, $F(1, 55) = 5.08$, $MSE = .04$, $n_p^2 = .09$, $p = .028$. Analogous to Experiment 4, this interaction reflected the fact that RGs tracked penalty-based changes in optimal bias better than NGs. That is, although both groups deviated substantially from optimal criterion setting, and although neither group adjusted their criterion as much as they should have as the penalty was manipulated, these problems were less for RGs than NGs. No other main effect or interaction was significant from this analysis, largest $F(1,55) = 2.31$, $MSE = .07$, $n_p^2 = .04$, $p > .05$.

Table 4.7

Mean Gambling Likelihood, Optimal Likelihood and Deviation as a Function of Group and Penalty Condition in Experiment 5.

Group	Gambling Likelihood	Optimal Likelihood	Deviation[a]
	Measure		
	Low-Penalty Condition		
NG	0.76 (.05)	0.92 (.02)	0.16 (.04)
RG	0.82 (.04)	0.95 (.01)	0.13 (.03)
	High-Penalty Condition		
NG	0.69 (.06)	0.16 (.03)	-0.53 (.08)
RG	0.58 (.06)	0.27 (.03)	-0.30 (.08)

Note: Standard errors of the means are in parentheses. NG = non-gamblers; RG = regular gamblers.

[a]This deviation measure corresponds to the deviation between the groups' optimal gambling likelihoods and their actual gambling likelihoods.

As in Experiment 4, the actual and optimal gambling likelihoods were plotted according to the individual sums for the three dice. These plots are shown in the left and right panels of Figure 4.2 for the low- and high-penalty conditions, respectively. The optimal gambling likelihood estimates per sum that are shown in the left panel of Figure 4.2 for the low-penalty condition indicate that RGs should be gambling almost 100 percent of the time on all of the sums. This is also generally true of NGs (except for the sum of 9 when they should be gambling less than half the time because their performance was particularly poor). Both groups showed a form of underconfidence, particularly for moderate sums, responding too conservatively (i.e., not gambling often enough to maximise their score). However, the RGs responded closer to optimal bias than NGs; for every single sum, RGs gambled more often than NGs, adopting a criterion setting that was closer to the optimal criterion setting.

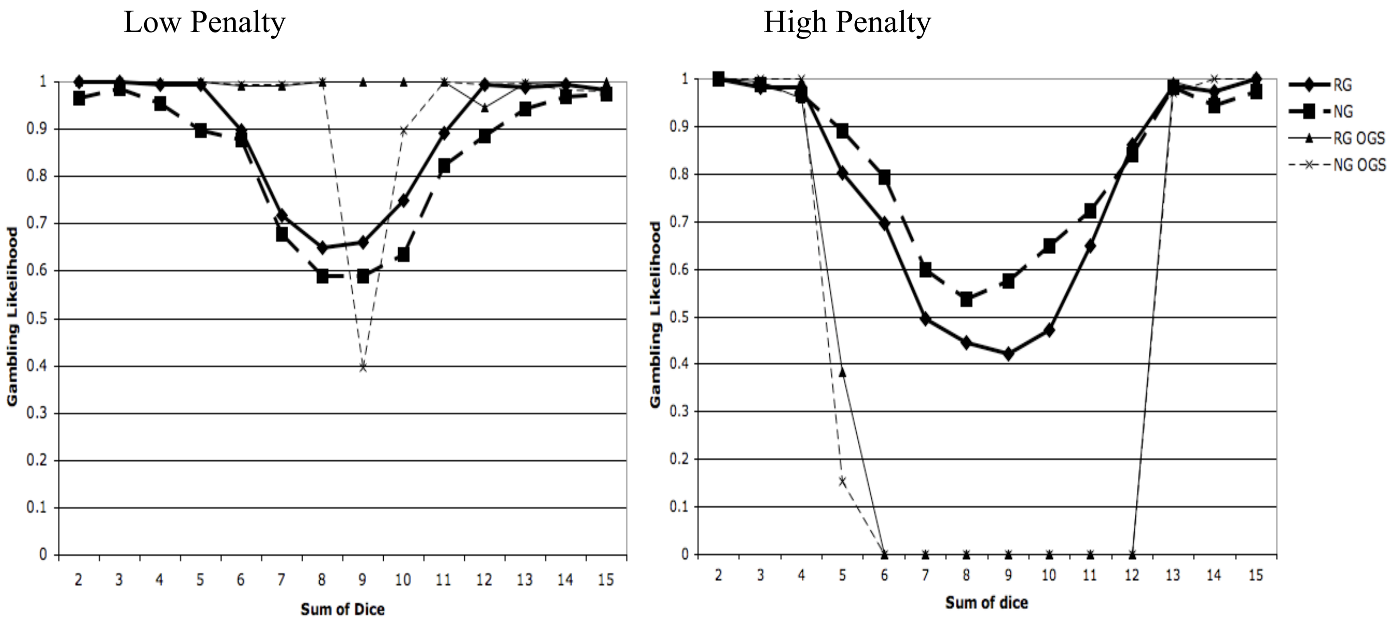

Figure 4.2. The sum plots of both groups in the low-penalty and high-penalty conditions of Experiment 5. RG = regular gamblers; NG = non-gamblers; OGS = optimal gambling setting.

The criterion shift that was discussed above is illustrated by comparing the left and right panels of Figure 4.2. Both RGs and NGs were quite liberal in the low-penalty condition gambling over 60 percent of the time for most sums. However, in the high-penalty condition (right panel), RGs in particular became much more conservative, with a sizable drop in their gambling likelihoods across the sums 5 to 12. The RGs became particularly cautious on the more difficult sum trials, presumably wanting to lessen the impact of the high penalty on their overall score. The NGs did not shift their gambling criterion on these difficult sums so efficiently. The consequence was that RGs "overtook" the NGs, being more liberal than NGs under low-penalty conditions, but more conservative under high-penalty conditions. Note that this behaviour meant that RGs were performing close to optimal bias in both penalty conditions.

These results indicate that both groups were unable to adopt a strategy to limit the effect of the high penalty so as to achieve positive scores (however the effect was lesser for RGs). Indeed, many of the participants in both groups completed the high-penalty task with a negative score (see Table 4.5) indicating that the gambling criterion was far from an optimal setting. As Figure 4.2 illustrates: participants in neither group should have gambled *at all* for sums 6-12, presumably because there was enough uncertainty surrounding the decision that the high penalty made gambling too risky. Had participants simply avoided the 'gamble' option altogether, their score would have improved (i.e., it would have been equal to zero).

Summary. The data from Experiment 5 indicate that the RGs demonstrated a greater sensitivity to the change in penalty for FAs than the NGs. The reason for this greater sensitivity is that the RGs tracked optimal gambling more effectively than the NGs, with much less deviation between their actual gambling likelihoods and their optimal gambling setting.

Thus, Experiment 5 indicates clearly that RGs' superior performance in Experiment 4 was not attributable to NGs being distracted by the high penalty. If anything, it was the RGs that were (appropriately) paying more attention to the increase in penalty in this experiment, not the NGs, lending further support to the expertise-transference hypothesis. However, it also indicates that there are limits to the benefits that gambling experience can afford if the ratio of rewards to penalties is low.

Discussion of Experiments 4 & 5

The present research investigated actual and optimal criterion settings of regular and novice gamblers in a probability-based gambling task using a type-2 SDT framework. The main objective of the study was to determine how RGs and NGs responded to manipulations of bias and how their gambling performance compared to optimal performance. According to the specificity hypothesis, despite regular practice at gambling activities, RGs are unable to transfer how they gamble to a novel task, leading to similar responsiveness to bias manipulations as NGs. As gambling is generally based on chance (with a small element of skill depending on the game), it may be very difficult for individuals who gamble regularly to transfer optimal strategies they have learnt in a gambling setting to a novel task.

Conversely, the expertise-transference hypothesis maintains that RGs, as a result of experience, can transfer what they have learnt about the impact of criterion setting on gambling success and are therefore more responsive to bias manipulations and perform more optimally than NGs. As long as gambling experience does not result in problem gambling, regular gambling could create competent gamblers who learn to make savvy decisions rather than overconfident gamblers largely insensitive to the dynamics of the game. In this way, gambling expertise develops in much the same way as other forms of expertise development, as long as the games that are practiced involve some element of skill (e.g., poker and blackjack instead of roulette and slot machines).

Experiment 4 manipulated rewards for correct gambles (Hs) and Experiment 5 manipulated penalties for incorrect gambles (FAs). Across both experiments, the expertise-transference hypothesis was given support. Compared to the NGs, RGs in both experiments were more accurate, set criteria that were closer to their optimal gambling criterion, and showed greater sensitivity to manipulations of bias.[6]

The Transference of Expertise

Given the scope of the studies, it is difficult to exact the skills being transferred from domain-specific to novel contexts. However, it appears that the RGs' increased understanding of how to organize and interpret information in a gambling context based on past experiences not only affects their ability to reason and problem solve, but also results in performing more accurately and more sensitively than the

NGs (Bransford, Brown & Cocking, 1999; Haskell, 2001). It is important to note here that we were not pre-selecting gamblers who played specific games of skill in order to find expert players who could set appropriate criteria for the task. We used a wide range of regular gamblers with various different gambling backgrounds of both 'skilled' (e.g., poker, blackjack) and 'chance' (e.g., slot machines, roulette) games, although the majority of RGs participated in both types of games. Experience in a domain does not contribute to expertise alone; other cognitive factors and strategies are required in order to perform with some level of expertise (Ceci & Liker, 1986). The findings suggest that our 'experts' have a much deeper conceptual understanding of the gambling domain, as they have been able to transfer their knowledge of probabilities and criterion settings from various games to a novel gambling task.

In a study examining type-1 criterion shifts, Parasuraman (1985) found that staff (expert) radiologists adjusted their disease-present/disease-absent criterion in response to a change in disease prevalence within a stimulus set, whereas resident (semi-expert) radiologists did not. This result accords well with our own. However, critically, Parasuraman's results were obtained with standard, stimulus-contingent discrimination (type-1 SDT), whereas ours were obtained with response-contingent discrimination (type-2 SDT). To our knowledge, our studies are the first to demonstrate expertise effects in type-2 criterion setting.

Additional research that explores *how* the RGs transfer their skills and the specific experiences that help them to perform more optimally on novel gambling tasks is required. It is conceivable that findings may yield useful information about causative factors that influence gambling behaviour and, perhaps more importantly, why some gamblers develop problematical tendencies.

Optimality and Extreme Criterion Setting

Despite the greater sensitivity to different bias manipulations observed for RGs compared to NGs in both experiments, virtually no participants in either group performed optimally. In Experiment 4, participants did not adequately take into consideration the relatively high penalty for FAs and tended to be overconfident (i.e., liberal) in their gambling decisions (Figure 4.1). Because the penalty for an incorrect gamble was so great compared to the rewards for correct gambles, it paid to avoid gambling unless there was relative certainty about the nature of the anomalous die. In Experiment 5, participants in the high-penalty condition also gambled too often, particularly for sums 5-12 (Figure 4.2). However, participants were underconfident (i.e., too conservative) in the low-penalty condition of Experiment 5. These participants presumably placed too much emphasis on the small penalty for FAs, failing to 'gamble' on a significant number of trials, whereas estimates of optimal gambling setting suggested that they should have been gambling across all sums almost 100 percent of the time.

The general pattern in Experiment 4 and the high-penalty condition of Experiment 5 of an overly liberal criterion setting, and an overly conservative criterion setting in the low-penalty condition of Experiment 5 is reminiscent of Higham's (2007) findings. He tested participants with multiple-choice questions from the 1997 Scholastic Aptitude Test (SAT) under two different incentive conditions: a low-incentive condition (+1 for Hs; -.25 for FAs) and a high-incentive condition (+1 for Hs; -4 for FAs). As in the current research, the point system could be avoided by opting to "guess" instead of "answer." Using bias profiles, he demonstrated that participants tended to be too conservative in the low-penalty condition but too liberal in the high-incentive condition, just as we found in our Experiment 5. More recently, Arnold, Higham, and Martin-Luengo (2011) have shown that formula-scoring systems with equal rewards for Hs and penalties for FAs (+1/-1) also show underconfidence (conservatism), despite repeated testing and feedback. These similarities between our current results and those obtained with educational testing occurred despite completely different tasks being used in the two lines of research. The similarities suggest that the failure to set criteria optimally is a fairly pervasive problem and likely stems from an inability to fully comprehend the impact of points on the final score or a reluctance to "go to the extremes" (i.e., a reluctance to nearly always gamble or nearly always guess, even though it may be beneficial to the final score). However, the fact that RGs demonstrated less of a problem than NGs in setting their criteria optimally suggests that these problems can be overcome, at least partially.

We believe that there is much to be gained from research on actual versus optimal criterion setting in type-2 SDT domains that are inherently metacognitive. Such research has the potential to be integrated with the growing literature on judgement heuristics, biases and cognitive failures relating to the irrationality of human subjects (e.g., Kahneman & Tversky, 1979; Lichtenstein & Fischhoff, 1977; Stanovich & West; 2000), and, more specifically, to the seemingly irrational beliefs and behaviour of problem gamblers (e.g., Breen, et al., 2001; Croson & Sundali, 2005; Gaboury & Ladouceur, 1989; Martins, Tavares, da Silva Lobo, Galetti & Gentil, 2004; Toplak, Liu, Macpherson, Toneatto & Stanovich, 2007; Wagenaar, 1988).

Limitations of the Current Research

It is possible that different motivations for gambling may exist between the RGs and NGs, and should be considered. It may be that the RGs revel in the competition of the game and so try harder than the NGs to succeed in winning the vouchers (e.g., Kuhberger & Perner, 2003; Lee, 2006), resulting in better performance on the task. Alternatively, the NGs could be over-focusing on potential gains or losses, which has resulted in sub-optimal criterion placement and is detrimental to their overall performance. However, in this vein, it is worth noting that the findings from both our experiments eliminate the possibility that the NGs are merely distracted by over-focusing on high penalties.

One feature that may distinguish our dice game from the games typically available in casinos and gambling venues is that it is possible to play our game strategically and at least break even (by, for example, "guessing" on every trial), whereas the casino games are designed to benefit the house. Thus, critics could argue that our game is not suitable for investigating "true" gambling performance. We believe two points are worth making in this regard. First, although breaking even on our task was possible, it was not a strategy that participants adopted. Most participants in both groups chose to gamble on a significant proportion of trials and many ended up with negative scores in both conditions of Experiment 4, and the high penalty condition of Experiment 5. Hence, it seems that our task was suitable for enticing gambling behaviour even when that behaviour was likely to end up with negative outcomes. Second, it is possible to improve the chances of winning by playing strategically in some casino games as well. For example, in games such as blackjack or poker, the odds against the player can be improved by, for example, wagering more money when a good hand has been dealt. Even games such as those on slot machines that seem like pure chance can be played strategically. For example, players can improve their chances of winning by "pinning" similar outcomes (e.g., two cherries) and only playing a third one instead of playing all three a second time. Thus, in our view, both our task and more typical gambling games contain both an element of chance and a strategic component.

It is possible that individuals who gamble for points rather than money, and participate in a lab rather than a real gambling venue, may make decisions differently (Anderson & Brown, 1984; Walker, 1992a, 1992b). However, we tried to account for this concern by encompassing £20 worth of vouchers as a 'jackpot' to encourage more realistic gambling behaviour.

Demographic and individual difference measures of the RGs and NGs were compared (Table 4.1) in order to rule out the existence of group differences that existed prior to any experiences with gambling. The analysis revealed that the groups had uneven gender differences (approaching significance in Experiment 4, and significant in Experiment 5), which could have attributed to differences in decision-making. Consequently, all measures were computed with and without gender as a between-participant variable and gender did not result in any main effects or interactions. We have, therefore, interpreted the differential group sensitivity to bias as due to a causal relationship of experience as gambling improves control over betting decisions.

Practical Implications and Conclusions

To conclude, whilst manipulations of points have been previously utilised in research of applications of type-1 and type-2 SDT to shift response criteria (e.g., sports betting settings, Erev et al., 1993; speech recognition settings, Gordon-Salant, 1985; and educational settings, Higham, 2007), a significant contribution of the present research is applying the type-2 SDT analysis to the gambling domain to investigate the role of expertise. We argue that type-2 SDT has been helpful in objectively assessing several underlying components of performance on the dice gambling task. SDT has a well-established methodology and holds the potential to help researchers understand not just the cognitive and metacognitive differences between RGs and NGs, but between these groups and problem gamblers as well (e.g., Lueddeke & Higham, 2011). In the long-term, SDT may be used as a screening tool to determine which cognitive/metacognitive skills need addressing in metacognitive therapy with problem gamblers (Lindberg, Fernie & Spada, 2011). In this way, we believe that type-2 SDT might be instrumental in quantitatively elucidating gambling and problem gambling behaviour, and, more generally, helping to probe further the effects of optimal criterion setting in decision-making under uncertainty.

CHAPTER 5
COGNITIVE AND METACOGNITIVE DIFFERENCES BETWEEN PROBLEM AND NON-PROBLEM GAMBLERS IN WAGERING TASKS[20]: EXPERIMENT 6

Most of the cognitive bias research to date has focused around games of chance, such as roulette and slot machines, rather than games with an element of skill, including poker and blackjack. However, some research has explored cognitive differences between gamblers on other gambling tasks, for example, the Iowa Gambling Task (Bechara, Damasio, Damasio, & Anderson, 1994) and general knowledge tasks (Lakey, Goodie & Campbell, 2006; Goodie, 2005). A number of studies have corroborated that problem gamblers (PGs) have demonstrably poorer decision-making, planning, and response inhibition (Cavedini, Riboldi, Keller, D'Annucci & Bellodi, 2002; Fischer & Smith, 2008; Goudriaan, Oosterlaan, de Beurs & van den Brink, 2005, 2006; Ledgerwood, Alessi, Pheonix & Petry, 2009; Ledgerwood et al., 2011; Petry, 2001b; Wagenaar, 1988).

Recently, Linnet et al. (in press, p. 2) proposed that poker players may suffer from 'more discrete cognitive biases of probability estimation and choice', rather than simply basing explanations on the traditional irrational beliefs often observed (such as an illusion of control or the gambler's fallacy). Linnet et al. reached this conclusion from research involving a simplified poker task in which participants were required to determine the objective probability of winning against a fictitious opponent and to 'play' or 'fold' the gamble. Moreover, they found that pathological and inexperienced gamblers demonstrated a larger error margin of probability estimation, played more hands of poker with less chance of winning, and had poorer differentiation of winning probability between played and folded hands than experienced (non-pathological) gamblers. The researchers used two main measures: estimation bias, defined as the difference between estimated probability and objective probability, and decision-bias, defined as the average probability of gambles.

Although these investigations are informative in elucidating differences between groups of non-problem and problem gamblers, Linnet and colleagues' research (in press; Linnet, Gebauer, Shaffer, Mouridsen & Moller, 2010), along with

[20] Article in preparation with Dr P. Higham, to be submitted to the Journal of Gambling Studies.

other gambling studies (e.g., Griffiths, 1994; Lawrence et al., 2009) has not taken into account a number of potentially important variables, for example, that the proportion of times a participant gambles (i.e., frequency of gambling; termed decision bias, or gambling likelihood; see Lueddeke & Higham, 2011). In addition, it may be argued that their findings may be contaminated by other factors that are individual to the groups, such as accuracy or prior knowledge. To illustrate the relevancy of this association, we would not be surprised if an experienced, non-problem gambling group turned out to be more accurate as a result of gambling more often.

Lueddeke and Higham (2011; Chapter 4) proposed an expertise-transference hypothesis to explain cognitive differences between RGs and NGs on a dice task. The hypothesis suggested that the RGs developed some expertise with gambling tasks through regular gambling, which resulted in gambling more appropriately on a novel dice task. The main analysis utilised a decision bias measure, which the researchers termed 'gambling likelihood' (the proportion of times a participant 'gambled' versus 'passed' a gambling trial, analogous to Linnet et al's (in press, 2010, decision bias measure). The findings demonstrated that the RGs were more accurate and more sensitive to bias manipulations of penalties and rewards compared to the non-gamblers. However, Lueddeke and Higham (2011) adopted principles from type-2 signal detection theory in order to ascertain whether the gambling likelihood measure was affected by variation in accuracy and to determine the optimality of both groups' gambling likelihoods. The gambling likelihood measure was attributed to actual changes in criterion (i.e., the proportion of gambles that shifted between penalty/reward manipulations) rather than group differences in accuracy.

High-wager likelihood (HWL) is a comparable decision bias measure to gambling likelihood, but instead of the gambler having a choice between whether to gamble or withhold, the gambler has a choice between whether to gamble with a high wager versus a low wager. HWL is defined as the proportion of high-wager bets (HWL = (Hs+FAs)/(Hs+Ms+FAs+CRs), and its suitability in quantifying decision bias that has not been contaminated by other variables is investigated in the present study. How other cognitive and metacognitive variables may influence the decision bias measure may be best illustrated with reference to some specific examples. One scenario underscores how accuracy may contaminate HWL. Suppose a gambler completes the task with 200 trials and achieves 50% accuracy, that is, regardless of how many high or low wagers the gambler has selected, 50% (100) of all the 200 decisions are correct (e.g., [Hs+Ms]/[Hs+Ms+CRs+FAs]=[80+20]/[80+20+80+20]). If the high-wager criterion were placed at the intersection point of the correct and incorrect item distributions, then the criterion based on computing the proportion of high wagers, would equal 50% ([Hs+FAs]/[Hs+Ms+CRs+FAs]= [80+20]/[80+20+80+20]). Now consider that in another condition the same gambler does not alter their gambling criterion, but achieves 65% (130) accuracy ([115+15]/[115+15+45+25]. This time the HWL is 70% [115+25]/[115+15+45+25]), suggesting that the gambler's criterion has shifted to become more liberal, when in fact it has not moved.

The gambler's resolution may also contaminate the HWL measure. A gambler, who is unable to discriminate effectively between their correct and incorrect decisions (poor resolution), will demonstrate very little difference between his/her HR and FAR, betting with many high wagers on incorrect decisions and many low wagers on correct decisions. Based on a hypothetical d' of 1.00 (with the correct and incorrect distributions close together), the HWL is 50% ([80+20]/[80+20+80+20]). However, someone who has better resolution (the model assumes the incorrect distribution is static and only the correct distribution moves if resolution increases), with a high HR and low FAR ($d' = 1.5$; similar accuracy and criterion to the poorer monitoring example), the HWL would be 58% [[95+20]/[95+5+80+20]). Hence, HWL (and GL) is potentially a problematic measure of criterion placement, and these examples highlight how we need to be cognizant of the possible influences of performance measures on decision bias/gambling likelihood measures. The significance of type-2 SDT infers that it is possible to resolve whether the HWL measure is influenced by the gambler's accuracy and/or resolution (which may result in observed differences between groups that are erroneously attributed to different criterion placements), by analyzing the FARs. The FARs are not affected in the same way as HWL because it is assumed that the incorrect distribution has not moved and nor has the criterion. Type-2 SDT can also be used to create bias profiles which allow us to observe how much gamblers' criteria deviate from how they should be gambling (optimal HWL, calculated the same way as optimal GL; Appendix A; see also Higham, 2007; Higham & Arnold, 2007a, 2007b):

Whilst some research has applied SDT to measure gambling behaviour (e.g., Clifford, Arabzedah & Harris, 2008; Dienes & Seth, 2009; Fleming & Dolan, 2010; Koch & Prueschoof, 2007; Persaud and colleagues, 2007, 2008), only one paper to date has utilised the type-2 SDT framework to explore differences between groups of gamblers (Lueddeke & Higham, 2011). One limitation of Lueddeke and Higham's research is that it did not include PGs.

Study Overview

The present study aimed to investigate cognitive variation between RGs and problem gamblers (PGs). The working hypothesis of this study is based on the following reasoning: if the two groups hold similar regular gambling exposure but demonstrate vast differences in the underlying mechanisms in which they make decisions, then insight may be gained in further understanding the aetiology of problem gambling. Type-2 SDT analysis was utilised to explore three main issues:

1. Whether differences in accuracy, resolution and gambling criterion could be observed between PGs and RGs.
2. Whether different cognitive biases may be observed in different gambling tasks.
3. Whether HWL measure is an appropriate measure of gambling criterion.

It is conjectured that the PGs will set less optimal FARs compared to the RGs, because previous research has indicated poorer decision-making and a lack of impulse control in PGs. If this is the case, we will be able to determine if these disadvantageous gambles are a result of a less optimal criterion, poorer accuracy and/or poorer resolution.

Participants were presented with two tasks: a probability-based dice task (Green & Swets, 1966; Lueddeke & Higham, in 2011) and a general knowledge task. The dice task was designed to resemble a task that can be played in a gambling venue whilst remaining novel for the participants. The general knowledge task has less of an element of randomness and generally does not resemble a chance-based task available in a gambling venue. It was anticipated that we would observe some differences in the gamblers' performances on each task.

Method

Participants

A total of thirty-six non-problem gamblers (aged between 18 and 62 years) and 33 problem gamblers (aged between 18 and 58 years) participated in counterbalanced tasks of the experiment (see Table 5.1 for the specific demographics for each group). The majority of participants were students or staff from the University of Southampton, with a minority of students from other UK universities (n = 7) or the general public (n = 3). Advertisements were placed around the University of Southampton's campus, on the Facebook (a popular social networking website) 'marketplace' and in the 'letters' section of a local newspaper.

Both groups gambled at least once a month on any gambling activities that involved money. These activities included gambling in casinos, betting shops, bingo halls, gaming venues, online or with friends. Exclusion criteria included individuals who gambled less frequently than once a month[21]; individuals who have been gambling regularly for *less* than 6 months; individuals who *only* played the National Lottery as a form of gambling; and individuals who have previously attended, or were currently attending professional treatment for their gambling behaviour. RGs were classified as individuals who scored between 0 and 3 on the SOGS; Appendix C), and PGs were classified as individuals who scored 4 or higher on the SOGS.

The majority of participants (92%) possessed an undergraduate degree or higher with no significant difference in educational attainment between the two groups, $t(63) = .01$, $p > .05$ (see Table 5.1 for the specific demographics of each group). The groups also did not differ in terms of their age, gender, depression score, how long they had been gambling on a regular basis, the age at which they were first introduced to gambling, and past or present problems with drugs (all ts = 0-1.93, ps >.05).

However, there was a significant difference between the groups in terms of their anxiety scores on the HADS, $t(63) = -2.18$, p =.03. PGs indicated higher levels of anxiety (M = 7.45, MSE = .68) than the NPGs (M = 5.75, MSE = .44), although the mean anxiety score for the PGs did not fall in the 'borderline' or 'problem' ranges. PGs also indicated significantly more problems with alcohol than the NPGs, $t(63) = 2.86$, $p = .01$.

[21]The term *regular gambling* in our experiments refers to gambling at least once a month for a period of more than 6 months.

Table 5.1

Demographics of the Non-Problem Gamblers and Problem Gamblers in the Dice and General Knowledge Tasks of Experiment 6.

	Dice Task		General Knowledge Task	
Demographics	RG	PG	RG	PG
n	36	29	35	33
Mean age	24.19	24.00	25.40	24.76
SD	8.66	6.52	10.73	8.60
Males	67%	76%	69%	76%
Education:				
School (16 years)	3%	0%	3%	3%
College (18 years)	3%	10%	6%	9%
Undergraduate	72%	66%	68%	67%
Postgraduate	22%	24%	23%	21%
SOGs score, *SD*	1.47 (1.03)	6.62 (2.91)	1.49 (1.04)	6.82 (3.02)
Duration (in months) gambling on a regular basis, *M (SD)*[a]	39.57 (63.53)	50.69 (61.25)	40.56 (64.42)	61.39 (94.89)
Age (years) first introduced to gambling, *M (SD)*	16.34 (4.19)	14.97 (3.95)	16.35 (4.34)	15.12 (3.76)
HADs:				
Anxiety score, *M (SD)*	5.75 (2.62)	7.45 (3.65)	5.89 (2.53)	7.33 (3.47)
Depression score, *M (SD)*	3.17 (2.64)	4.48 (2.86)	3.37 (2.69)	4.39 (2.73)
Alcohol Problem[22]	6%	28%	6%	27%
Drugs Problem	6%	14%	6%	12%

Note: RG = Non-problem gamblers; PG = Problem gamblers; SOGS = South Oaks Gambling Screen; HADS = Hospital Anxiety and Depression Scale.

[22] A formal assessment of an alcohol or drug problem was not undertaken. These percentages relate to the participants' subjective perceptions of whether they have previously had, or currently have a 'problem' with either drugs or alcohol.

These are somewhat unsurprising findings as problematic gambling has been co-morbidly associated with alcohol use disorders (Grant, Kushner & Kim, 2002), as well as other psychiatric disorders such as drug dependence, mood, and personality disorders (e.g., Ibáñez et al, 2001).

In a study of over 43,000 participants, Petry, Stinson and Grant (2005) found that 73% of pathological gamblers had an alcohol use disorder and 41% had an anxiety disorder. It would be difficult to recruit a group of problem gamblers without the associated substance/mood disorders, but these comorbid disorders should be taken into consideration when reviewing the findings. Two RGs and one PG discontinued the study after the dice task, and one RG and three PGs discontinued after completion of the general knowledge task.

Design and Materials

The HADs and the SOGS (see Appendix B and C, respectively; for full description of the questionnaires see Chapter 4) were administered to each of the participants prior to the computerised wagering tasks. Two computerised wagering tasks were created for this experiment: a dice task and a general knowledge task, which were counter-balanced to avoid order effects. In both tasks participants were required to make three choices on each trial. First, participants were forced to make a decision between two alternative answers (2AFC). Second, they decided whether to bet with 'high' or 'low' wagers on their decision. High and low wager structures were manipulated across three conditions (see Table 5.2) to create a High Optimality (HO) condition, a Medium Optimality (MO) condition, and a Low Optimality (LO) condition. The selection of these particular parameters was based on pilot data, indicating that optimal bias was likely to vary considerably between the experimental conditions if they were used, with the condition names representative of the proportion of times participants *should* be gambling with high wagers. For instance, using bias-profile methodology (see Appendix A), in the High Optimality condition, based on an average d' (resolution measure) of 1.00 and average decision accuracy of 67%, participants should be gambling approximately 79% (a high proportion) of the block of trials with high wagers. Accuracy of 67% was chosen as that matched accuracy in a previous norming and empirical studies (e.g., Lueddeke & Higham, 2011). A d' of 1.00 was chosen as it was in the middle of a low d' observed in the dice task, and a high d' observed in the general knowledge task (based on previous norming studies). Monitoring the accuracy of candidate answers retrieved from memory is no doubt a richer process (e.g., cued recall: Higham, 2002; Higham & Tam, 2005; old/new recognition: Higham et al., 2009; 2AFC recognition: Higham, Luna, & Bloomfield, 2010; or retrieval of general knowledge: Higham & Gerrard, 2005), than monitoring the accuracy of probabilistic decisions in the dice game. Finally, a confidence rating was taken between 1 (low confidence) and 6 (high confidence) on the accuracy of each decision.

Table 5.2

The Wager Structures of each Condition for the Dice and General Knowledge Tasks.

	High Wager		Low Wager		OHWL[23]
Condition	Correct (H)	Incorrect (FA)	Correct (M)	Incorrect (CR)	
High Optimality	+5	-5	+1	-1	79%
Medium Optimality	+5	-5	+4	-2	43%
Low Optimality	+2	-5	+1	-1	33%

Note: These Optimal HWLs are based on predicted d' of 1.00 and predicted accuracy of .67. The Medium and Low Optimality conditions were pooled together in the analyses to create one 'Low Optimality' condition, because the groups gambled similarly in the conditions of both tasks. H = hit, FA = false alarm, M = miss, CR = correct rejection, OHWL = Optimal High-Wager Likelihood.

Dice task. Participants were presented with the dice task (inspired by Green & Swets, 1966) that was reported in the methodology of Chapters 3 and 4 (see also Lueddeke & Higham, 2011). The only element that differed in the present experiment is that participants had the option of selecting either 'high wagers' or 'low wagers' on their gambling decisions. In the previous experiments, participants selected either the 'gamble' or 'guess' option. Each condition (HO, MO, LO) consisted of 144

[23]Whereas the accuracy of the predicted OHWLs in the table were relatively similar to the actual accuracies obtained by participants on both tasks, the d' (d-prime) for the groups were substantially lower than 1.00 for both the dice and general knowledge tasks. Therefore, the actual OHWL for each group differs from the estimated percentages shown here (see Tables 5.4 and 5.5 for the OHWL for each group in the two tasks).

experimental trials and the trials were presented in a single random order to all participants. To generate these trials, sums associated with all 72 (6 x 6 x 2) possible combinations of the three dice were presented to participants twice per condition (72 x 2 = 144). This presentation method meant that participants viewed sums that corresponded to the throwing of fair dice (i.e., each face on each die had a one-sixth probability of contributing to the presented sum). Participants completed this task in approximately one hour.

General knowledge task. The other task involved the presentation of general knowledge questions and participants were required to select an answer from two alternatives. Each condition consisted of 50 questions that were randomly presented to participants and lasted approximately 45 minutes.

The question lists were constructed based on a norming study prior to the present experiment. One hundred and fifty of 222 questions were selected to form three lists of 50 questions that were balanced both in terms of accuracy (all lists: 66% accuracy; $F(2, 149) = .001$, $p > .05$) and mean confidence (list 1: 3.61, list 2: 3.56, list 3: 3.67; $F(2, 149) = .15$, $p > .05$). These lists were counterbalanced between conditions.

Procedure

The experiment was conducted online in order to gain access to a greater number of PGs. Participants who indicated an interest in the study were sent a link allowing them to participate. The opportunity for participants to complete the wager tasks at their own convenience was seen as an advantage for the study in that the task environment had greater ecological validity (similar to Internet gambling). Participants were instructed to situate themselves in a quiet room with no people or audio distractions, and to increase the volume on their computer so they could clearly hear the audio feedback.

The first part of the experiment required participants to check an online informed consent form and to complete demographic questions, gambling behaviour questions, the SOGs, and HADS. Participants were then directed to one of the wager tasks (random allocation). Participants were initially required to complete five practice trials to become accustomed to each task before actual play. The HO, MO and LO conditions were then administered in a counterbalanced order. The trials were self-paced and the participants could have a break in between the trials for a maximum period of five minutes. Participants were given immediate feedback on their responses in the form of a 'points' box in the top right of the computer screen accompanied by either a 'ding' or 'buzzer' sound to indicate a correct or incorrect answer, respectively. After completion of the first task, participants were then directed to the second task that they could complete immediately, or have a rest and return to later.

A debriefing statement revealing the main hypotheses of the experiment followed completion of the second gambling task. Information on where to seek help with gambling problems, if needed, was also supplied with the debriefing statement. Participants were paid £10 for completion of both tasks and an incentive of £20 worth of vouchers was offered to the highest scoring individual of the dice task, in order to encourage more realistic gambling behaviour[24].

Dice Task Results

Preliminary analyses demonstrated that the LO and MO conditions produced comparable performance. Therefore, for simplicity regarding the analyses, these two conditions were pooled together to create one 'LO' condition for both the dice task and the general knowledge task results.

Accuracy and Confidence

Overall accuracy across all trials was computed for each participant (see Table 1.2 for the calculation, and Table 5.3 for the means and SEs). A 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA was conducted on the accuracy data, with condition as within-subject variable. The ANOVA revealed a significant main effect of group, $F(1, 63) = 10.55$, $MSE = .01$, $\eta_p^2 = .14$, $p < .01$. The RGs had significantly higher accuracy ($M = .70$, $SEM = .01$) than the PGs ($M = .65$, $SEM = .01$).

The main effect of condition and the condition by group interaction were not significant, largest $F(1, 63) = 3.56$, $p = .06$. The same set of sums were presented in

[24] This incentive was only offered to the highest scoring individual in the dice task. An incentive was not offered for the general knowledge task as participants may have been able to look up the correct answers to questions on the Internet, or ask their friends. Instead, participants were instructed to not seek out any information from other sources in answering the general knowledge questions, but to try their best to score as high as possible.

each of the conditions, and the conditions were counterbalanced, so mean accuracy across the conditions was expected to be similar.

Table 5.3

Mean Accuracy and Confidence Rating as a Function of Group and Wager Condition in the Dice and General Knowledge Tasks.

	Dice Task		General Knowledge Task	
Group	Accuracy	Confidence	Accuracy	Confidence
	High Optimality condition			
RG	.70 (.01)	3.88 (.14)	.75 (.02)	3.70 (.16)
PG	.65 (.01)	4.33 (.15)	.72 (.02)	4.13 (.16)
	Low Optimality condition			
RG	.69 (.01)	4.07 (.15)	.73 (.02)	3.88 (.14)
PG	.65 (.01)	4.47 (.14)	.71 (.02)	4.24 (.14)

Note: Standard errors of the means are in parentheses. RG = non-problem gamblers; PG = problem gamblers.

A 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA was conducted on the overall confidence data for each condition (see Table 5.3 for the means and SEs), with condition as the within-subject variable. The main effect of group was significant, $F(1, 63) = 5.55$, $MSE = 1.06$, $\eta_p^2 = .00$, $p = .02$, which demonstrated that the PGs confidence ($M = 4.40$, $SEM = .14$) was greater than the RGs ($M = 3.97$, $SEM = .12$), despite the PGs being significantly less accurate than the RGs (accuracy analysis). The main effect of condition was also significant, $F(2, 63) = 5.32$, $MSE = .16$, $\eta_p^2 = .08$, $p = .02$. Confidence was significantly greater in the LO condition ($M = 4.27$, $SEM = .09$) compared to the HO condition ($M = 4.10$, $SEM = .10$). It is conceivable that the HO condition was perceived by the participants to be higher risk due to the reward and penalty extremes between the high and low wagers (i.e., plus or minus 5 points for high wager decisions and plus or minus 1 point for low wager decisions), even though it was the ‘easiest’ condition in terms of the potential to gain points. The condition by group interaction was not significant, $F < 1$.

Considered collectively, the above results display a confidence-accuracy disassociation. The RGs are more accurate than the PGs, but the better accuracy is coupled with lower confidence. Hence, the PGs are demonstrating overconfidence in their gambling decisions. This disassociation could be due to PGs having a problem discriminating between their correct and incorrect decisions (resolution), for instance, the PGs may be systematically assigning high ratings of confidence to incorrect responses. Alternatively, PGs could be having difficulty in setting their gambling criterion, generally assigning higher confidence to all decisions, regardless of accuracy. Type-2 SDT analyses will be used to distinguish between these possibilities by examining resolution and gambling criterion in the next section of the results.

Type-2 SDT Measures

Resolution. 0.5 was added to all frequency cells prior to the *d′* analysis to avoid undefined HRs and FARs, as in Chapters 2 and 3 (Fleming & Dolan, 2010; Hautus, 1995; Macmillan & Creelman, 2005; see formula 5 for calculation of *d′* and Table 5.4 for the means and SEs). A 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA on *d′*, with repeated measures only on the former factor, revealed a main effect of group, $F(1,63) = 7.32$, $MSE = .25$, $\eta_p^2 = .10$, $p = .01$. The RGs (M = .70, SEM = .06) were able to more effectively discriminate between their correct and incorrect decisions compared to the PGs (M = .47, SEM = .07). The main effect of condition was also significant, $F(2,63) = 8.84$, $MSE = .08$, $\eta_p^2 = .12$, $p < .001$. Resolution performance in the LO condition (M = .66, SEM = .05) was significantly greater than resolution performance in the HO condition (M = .51, SEM = .05). The wager structure of the HO condition presumably meant the participants did not have to be so stringent in monitoring their correct and incorrect decisions. Finally, the ANOVA yielded a significant condition by group interaction, $F(1, 63) = 7.59$, MSE = .08, $\eta_p^2 = .11$, $p = .01$. This interaction came about because the resolution difference between the HO and LO conditions was greater for the RGs compared to the PGs.

FAR. A 2 (group: RGs, PGs) X 2 (condition: HO, LO) mixed ANOVA on FAR, with repeated measures on the condition variable was conducted as a measure of criterion. The analysis yielded a main effect of condition, $F(1,63) = 31.43$, MSE = .05, $\eta_p^2 = .33$, $p < .001$, with a greater amount of FAs committed in the HO condition (M = .49, SEM = .05), compared to the LO condition (M = .27, SEM = .03). The participants were correctly gambling more conservatively in the LO condition. The RGs (*M* = .31, *SEM* = .04) also set a more conservative gambling criterion than the PGs (*M* = .46, *SEM* = .05), shown by the lower proportion of FAs, which was demonstrated by a main effect of group, $F(1,63) = 5.11$, $MSE = .14$, $\eta_p^2 = .08$, $p < .03$. The condition by group interaction was not significant, $F(1, 63) = 2.25$, $p = .14$.

Table 5.4

Mean Resolution, FAR and HWL as a Function of Group and Wager Condition in the Dice Task.

	Measure		
Group	Resolution (*d′*)	FAR	HWL
	High Optimality condition		
RG	.56 (.07)	.58 (.05)	.45 (.06)
PG	.46 (.08)	.64 (.05)	.54 (.07)
	Low Optimality condition		
RG	.85 (.06)	.35 (.04)	.19 (.05)
PG	.47 (.07)	.48 (.05)	.38 (.05)

Note: Standard errors of the means are in parentheses. RG = regular gamblers; PG = problem gamblers; HWL = high-wager likelihood; FAR = false alarm rate.

High-Wager Likelihood. In order to determine whether the HWL measure was a good indication of criterion shifts, or whether the measure was contaminated with group differences in accuracy and monitoring, a 2 (group: RGs, PGs) X 2 (condition: HO, LO) mixed ANOVA on HWL, with condition as the within-subject variable, was conducted (see Table 5.4). HWL was calculated using the following formula:

$$HWL = (Hs+FAs)/(Hs+Ms+FAs+CRs)$$

The analysis yielded a main effect of group, $F(1, 63) = 4.37$, $MSE = .09$, $\eta_p^2 = .07$, $p = .04$, showing that the PGs (*M* = .56, *SEM* = .04) were setting a more liberal gambling criterion than the RGs (*M* = .45, *SEM* = .04) throughout the dice task. A main effect of condition, $F(1. 63) = 36.87$, $MSE = .04$, $\eta_p^2 = .37$, $p < .001$, showed that in general, participants were gambling with high wagers more often in the HO condition (M = .61, SEM = .04) condition compared to the LO condition (M = .40, SEM = .03). This finding is expected because the HO condition was essentially the easiest condition, with a greater number of high wagers required in order to perform optimally. This analysis was comparable to the FAR analysis and signifies that HWL in the dice task was not influenced by the other performance measures.

General Knowledge Task Results

Accuracy and Confidence

As in the dice task results, a 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA, with condition as the within-subject variable, was conducted on the general knowledge task accuracy data (see Table 5.3 for the means and SEs). The results did not reveal a significant main effect of group or condition, and there was no interaction, largest $F(1, 66) = 3.35$, $p = .07$. The main effect of condition was approaching significance. There were no accuracy differences between the RGs and the PGs, which differs from the dice task findings.

A 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA was conducted on the confidence data (see Table 5.3 for the means and SEs), with condition as the within-subject variable. The main effect of group was significant, $F(1, 66) = 4.12$, $MSE = 1.34$, $\eta_p^2 = .06$, $p = .05$, which demonstrated greater PG (M = 4.19, SEM = .14) confidence compared to the RGs (M = 3.79, SEM = .14). The main effect of condition was also significant, $F(1, 66) = 4.35$, $MSE = .16$, $\eta_p^2 = .06$, $p = .04$, with a similar trend that was observed in the dice task: lower confidence in the HO condition (M = 3.92, SEM = .11) compared to the LO condition (M = 4.06, SEM = .10). The condition by group interaction was not significant, $F < 1$. These confidence findings are consistent with the statistical confidence data observed in the dice task results.

Type-2 SDT measures

Resolution. A 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA on d', with repeated measures only on the former factor, did not reveal any main effects or an interaction, although the main effect of group was approaching significance, largest $F(1, 66) = 2.86$, $p = .10$. The resolution findings for the general knowledge task (see Table 5.5 for means and SEs) differ from the dice task findings in which the RGs demonstrated better resolution than the PGs.

FAR. A 2 (group: RGs, PGs) X 2 (condition: HO, LO) mixed ANOVA (see Table 5.5 for means and SEs) with condition as the only within-participants variable, yielded a main effect of condition, $F(1,66) = 23.45$, $MSE = .03$, $\eta_p^2 = .26$, $p < .001$. There was a greater number of FARs in the HO condition ($M = .46$, $SEM = .03$) compared to LO condition ($M = .32$, $SEM = .03$). The analysis also revealed a main effect of group with a stricter criterion set by the RGs ($M = .29$, $SEM = .04$) compared to the PGs ($M = .49$, $SEM = .04$), $F(1, 66) = 10.96$, $MSE = .12$, $\eta_p^2 = .14$, $p < .01$. The condition by group interaction was approaching significance, $F(1, 66) = 3.80$, $p = .06$, which resulted from a smaller FAR difference between the conditions for the RGs in comparison to the PGs. In essence, the PGs appear to be almost too sensitive to the wager manipulations and have shifted their gambling criteria more than the RGs.

Table 5.5

Mean Resolution, FAR and HWL as a Function of Group and Wager Condition in the General Knowledge Task.

	Measure		
Group	Resolution (*d'*)	FAR	HWL
	High Optimality condition		
RG	.93 (.09)	.33 (.05)	.58 (.04)
PG	.67 (.09)	.25 (.04)	.74 (.04)
	Low Optimality condition		
RG	.88 (.09)	.58 (.05)	.48 (.04)
PG	.81 (.08)	.39 (.04)	.60 (.04)

Note: Standard errors of the means are in parentheses. RG = non-problem gamblers; PG = problem gamblers; FAR = false alarm rate; HWL = high-wager likelihood.

High-wager Likelihood. Again, an analysis of HWL was conducted to determine the suitability of HWL compared to the FAR analysis as a measure of gambling criterion. A 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA, with condition as the within-subject variable, which revealed a main effect of group, $F(1, 66) = 8.10$, $MSE = .08$, $\eta_p^2 = .11$, $p = .01$, which demonstrates that the PGs (M = .67, SEM = .04) are gambling with a greater proportion of high wagers than the RGs (M = .53, SEM = .04), and emulates the dice task findings (see Table 5.5 for means and SEs). The ANOVA also yielded a main effect of condition, $F(1, 66) = 47.79$, $MSE = .01$, $\eta_p^2 = .42$, $p < .001$, which confirmed that the participants were gambling with high wagers more often in the HO (M = .66, SEM = .03) condition compared to the LO condition (M = .54, SEM = .03). The condition by group interaction was not significant, $F(1, 66) = 1.46$, $p = .23$. These findings are analogous to the dice task HWL analysis, and again mirror the findings of the FAR analysis.

Discussion of Experiment 6

The present study investigated cognitive and metacognitive differences between RGs and PGs in two different wagering tasks: a dice task and a general knowledge task. The dice task superficially emulated a task that can be played in casinos; the general knowledge task was superficially different to casino games. Both tasks had the same game layout, and rewards and penalties for low and high wager gambles were manipulated across three conditions in each task. It was expected that the PGs would select more disadvantageous gambles compared to the RGs.

The LO and MO conditions were pooled together after preliminary analyses indicated that the participants were performing similarly in each of the conditions. The dice task results identified a confidence-accuracy disassociation. The RGs reported lower confidence but had higher accuracy than the PGs, and, to the contrary, the PGs reported higher confidence but displayed lower accuracy than the RGs. The overconfidence of PGs was also observed in the general knowledge task results. A type-2 SDT framework was used to determine which factors accounted for this variance. The analyses on the dice task data showed that the PGs suffered from both poor resolution and poor criterion placement, which was too liberal for the demands of the task, particularly in the LO condition. It was apparent that the PGs were reluctant to gamble with low wagers.

The accuracy and resolution differences that were observed between groups in the dice task were not evident in the general knowledge task. The PGs clearly have the potential to gamble more accurately and with better discrimination but are not doing so on the dice task. However, in a similar finding to the dice task, the PGs are also setting a more liberal gambling criterion in the general knowledge task, compared to the RGs. Hence, these findings infer that the superficial aspects of the task cause poor gaming behaviours in relation to accuracy and resolution, but gambling more often and overconfidence are general impairments that the PGs exhibit, regardless of the type of task.

SDT can also be used to determine what the optimal FAR is by the following formula:

Gambling score = f*(Hr*HR + Mr*(1-HR)) – (1-f)*(FAp*FAR + CRp*(1-FAR))
(where Hr = hit reward, Mr=miss reward, FAp = false alarm penalty and CRp = correct rejection penalty)

HR is then substituted with Φ(zFAR + *d′*) to get:

Gambling score = f*(Hr*Φ(zFAR + *d′*) + Mr*(1-Φ(zFAR + *d′*))) – (1-f)*(FAp*FAR + CRp*(1-FAR))

The FAR is then varied from 0 to 1 and the optimal FAR is the one associated with the highest gambling score.

Calculating the optimal likelihood per participant was not possible for all cases as many of the participants had HRs and/or FARs equal to 1.0 or 0, which renders *d′* as undefined (see Macmillan & Creelman, 2005). Therefore, optimal FAR was calculated using group means as opposed to individual participant means (see Table 5.6 for the group optimal FARs and absolute deviation scores).[25] The individual FARs were then subtracted from the group optimal FARs for each task to compute individual absolute deviation scores from optimal FAR. The deviation scores were analysed in a 2 (condition: HO, LO) X 2 (group: RGs, PGs) mixed ANOVA, with group as the only between-participants variable. The ANOVA on the dice task revealed a main effect of condition, $F(1, 63) = 13.38$, $MSE = .12$, $\eta_p^2 = .18$, $p = .001$, with the groups deviating further from their optimal FAR in the HO condition (M =

[25] Optimal FAR had to be calculated for the LO and MO conditions separately because of the different wager structures associated with each condition. The average of the two condition optimal FARs was then taken to calculate deviation from group optimal FAR as the data for the two conditions were pooled into one condition for the analysis.

.47, *SEM* = .25) compared to the LO condition (*M* = .25, *SEM* = .03). This finding was replicated in the general knowledge task, $F(1, 66) = 15.27$, $MSE = .07$, $\eta_p^2 = .19$, $p < .001$.

The main effect of group was not significant for either the dice or general knowledge task, although the main effect of group was approaching significance in the dice task, $F(1, 63) = 2.78$, $p = .10$ ($F < 1$ for the general knowledge task). Importantly, both analyses also resulted in a significant condition by group interaction, $F(1, 63) = 6.69$, $MSE = .12$, $\eta_p^2 = .10$, $p = .01$ and $F(1, 66) = 4.14$, $MSE = .07$, $\eta_p^2 = .06$, $p = .05$, for the dice and general knowledge tasks, respectively. Across the HO condition in two tasks, the participants gambled comparably and they were both too conservative and deviated considerably from their optimal FAR. The HO condition required participants to set a very liberal gambling criterion (with a high proportion of high wagers almost 100% of the time) in order to optimise their points. In fact, the PGs almost demonstrated an advantage in this condition as they gambled with a higher proportion of high wagers compared to the RGs. This finding is noteworthy as PGs are able to show underconfidence (gambling too conservatively) when optimal high-wager gambling rates are very high; thus, even PGs have their limits.

Table 5.6

Mean Optimal FAR and Absolute Deviation from Optimal FAR as a Function of Group and Wager Condition in the Dice and General Knowledge Tasks.

	Dice Task		General Knowledge Task	
Group	Optimal FAR	Deviation from FAR	Optimal FAR	Deviation from FAR
	High Optimality condition			
RG	.95	.52 (.06)	.75	.44 (.04)
PG	.99	.42 (.07)	.91	.34 (.05)
	Low Optimality condition			
RG	.17	.13 (.04)	.24	.16 (.03)
PG	.01	.36 (.04)	.20	.25 (.03)

Note: Standard errors of the means are in parentheses. RG = non-problem gamblers; PG = problem gamblers; FAR = false alarm rate.

It is in the LO condition where the two groups differ. The LO condition requires participants to set a very conservative gambling criterion and the RGs are closer than the PGs to their optimal FARs in this condition. If we generalise the study findings to an actual gambling context, lower gambling rates are required, and it is on these occasions that PGs struggle to perform well.

The difficulty for PGs in setting appropriate FARs in the LO condition, along with overconfidence in their decisions is underscored by previous research on cognitive biases, which has demonstrated that when some individuals are faced with a risky, uncertain decision, they poorly calibrate their decisions and are often overconfident (e.g., illusion of control, Langer, 1975; Moran, Ariás and Salguero, 2003). Goodie (2005) used a betting paradigm to explore differences in calibration between problem and non-problem gamblers. Participants were required to place bets on general knowledge questions and to indicate how confident they felt that their answer was correct. The findings confirmed that there was greater acceptance of risk as probability increased, demonstrated by the problem gamblers' overconfidence in their decisions (more willing to bet), resulting in earning fewer points. Goodie's results accord well with our own whereby the PGs set a much more liberal gambling criterion, with greater confidences, despite displaying worse accuracy than the RGs in the dice task.

Diskin and Hodgin (1999) suggested that problem gamblers' level of arousal is maintained by narrowed attention and intense concentration (see also Lobo, Stewart, Klein & Blackburn, 2004). Perhaps, realising they were in a simulated gambling environment, the PGs had a shorter attention span or lost interest over the course of the dice task compared to the general knowledge task. To determine whether boredom contributed to the PGs' poor accuracy and resolution in the dice task, one-way repeated measures ANOVAs were conducted on both the accuracy and resolution measures across the three blocks of trials (ordered according to serial position). The analysis indicated no significant effect of block order on accuracy for the RGs or PGs, $F(2, 70) = 1.58$, $p > .05$ and $F(2, 56) = 2.174$, $p > .05$, respectively. Further, there was no significant effect of block order on resolution for the RGs, $F(2, 70) = 1.28$, $p > .05$, or the PGs, $F(2, 56) = 1.05$, $p > .05$. Both groups' performances remained relatively stable across each condition, with little evidence to suggest that the PGs were bored with the task. However, in hindsight it would have been informative to record reaction time per trial as the PGs may have spent a shorter amount of time on the dice task if they were disinterested (little thinking time and strategic gambling). However, recording reaction time would have been difficult due to the online methodology.

It is conceivable that the nature of the dice task is more strongly associated with gambling in casinos, and as one consequence, the PGs may more easily fall into rash or irrational thought processing that they experience with casino games (e.g., Breen et al., 2001; Croson & Sundali, 2005; Gaboury & Ladouceur, 1989). On the other hand, it can be argued that the general knowledge task – more attuned to expectations of the general population - demands personal reflection and logical thought processing in unfamiliar territory. The finding that PGs perform less well in chance outcome versus semantic knowledge tasks in a simulated environment is a concern as this behaviour may generalise or translate to actual gambling activity. Griffiths (1999) suggested that structural characteristics of electronic gaming machines (EGMs), such as the speed of play, frequent wins, 'near misses', lights, and sounds, contribute to their addictive properties (see also Breen, 2004; Breen & Zimmerman, 2002; Loba et al., 2002; Morgan, Kofoed, Buchkoski & Carr, 1996; Turner & Horbay, 2004). Both the tasks used in this study incorporated quick game play and a short gap between gambles, but it was the nature of the tasks (probabilistic vs. semantic knowledge) rather than the structural characteristics that accounted for the differences in accuracy and resolution of the PGs. Without the use of type-2 SDT, it would have been difficult to separate each of the performance components and to determine the impairment of PGs' game play. Further research that explores differences between gambling activities to explore their addictive properties may be appropriate for gambling policy.

Analysis on HWL supported the FAR analysis, suggesting that the decision bias measure that is often used in gambling research (e.g., Linnet et al., in press, 2010, 2006; Lueddeke & Higham, 2011) appears to be a good measure of criterion placement, at least in analysing gambling tasks. Analyses that use SDT should be considered as they hold the potential to separate decision bias from resolution, and these distinctions may make a significant difference in the understanding of the underlying cognitions of PGs (whether conscious or unconscious), and possibly have treatment implications. Whilst this research is still in its early stages, the construction of bias profiles may also be informative in regulating how over- or under-confident PGs are when gambling, and determining the extent of their cognitive biases.

Limitations

The study is not without limitations. First, it could be argued that the greater anxiety and depression scores, or the higher incidence of drugs, of the PG group could contribute to the weaker performance of the PGs compared to the RGs. Despite the mean anxiety and depression scores falling in the normal range, it is a possibility that mood and drugs could have altered the PGs' decision-making abilities, and so our findings should be interpreted with some caution. However, very few differences in accuracy and resolution were found between the groups in the general knowledge task, suggesting that the specific nature of the tasks may have more of an impact on PGs' decision-making behaviour than mood or substance dependence factors. Moreover, the fact that we found these differences between the groups signifies a more ecologically valid sample (see Grant, Kushner & Kim, 2002; Ibáñez et al, 2001; Petry, Stinson and Grant, 2005, for discussions about comorbidity of substance abuse, mood, and psychiatric illnesses with problem gambling).

Secondly, the use of student participants rather than a clinical population could also be a shortcoming of the study. However, we decided that recruiting groups of gamblers from the same population (university) would help to reduce any background or educational differences between the participant groups and would, consequently, make a more successful basis for comparison (see Gainsbury & Blaszczynsky, 2010, for an in-depth discussion of the appropriateness of using students in gambling research). Further, there is a higher gambling incidence in the student population compared to the general population, with students identified by researchers as a high-risk and vulnerable population for developing problems with gambling (Delfabbro, 2008; Jacobs, 2004). The fact that we found differences between the groups raises the question of whether a clinical population would perform much worse on each of the test measures, particularly on the general knowledge task.

Conclusions

To conclude, the findings from this experiment imply that the PGs are impaired on accuracy and resolution when engaging in tasks that superficially resemble those that are played in casinos, but not if the games are superficially different. The problems that PGs experience with bias and confidence are more general deficits, rather than task-specific. The study findings offer evidence that it may depend on the type of task presented to participants that distinguishes group differences in accuracy and resolution. The study, therefore, highlights the need to separate these aspects of performance using SDT.

While the interplay between key performance measures (accuracy, resolution FAR and HWL) and experience requires further investigation in gambling contexts, we believe the present research provides a step forward in understanding the decision-making and executive functioning of different groups of gamblers. SDT provides a critical role in interpreting these differences. The findings offer further evidence for considering metacognitions and correcting bias in gambling treatment programs (Fischhoff, 1982; Lindberg et al., 2011; Morán et al., 2003).

CHAPTER 6
THE IMPACT OF FEEDBACK ON METACOGNITIVE PROCESSES IN GAMBLING: EXPERIMENT 7

The studies outlined in the past two chapters found distinct cognitive and metacognitive differences between groups. Specifically, differences in accuracy and gambling likelihood were observed between regular gamblers and non-gamblers (Experiments 4 & 5), and differences in accuracy, resolution and criterion setting were shown between regular gamblers and problem gamblers (Experiment 6). Considered collectively, it was concluded that regular gamblers are generally more sensitive to the demands of the dice task, likely as a consequence of regular participation in non-problematical gambling. And, secondly, because of their prior experience with gambling, they are able to shift their gambling criterion to a more optimal position with the manipulation of penalties, rewards and wager structures (which incorporates the manipulation of both penalties and rewards). While the findings of the previous chapters gave some insight into the underlying mechanisms that produced the differences between the groups, they also raised fundamental questions. One of these may be central to understanding the interplay between decision-making and optimal gambling performance. In short, the results of the experiments may lead us to the following question: If some individuals (RGs) are able to perform more optimally than others in the dice task, is it possible to train individuals who do not perform optimally to improve their decision-making through feedback on their gambling performance?

In order to address this research question, a new experimental design was constructed utilising the dice task, which incorporated a training block of trials. The study aimed primarily to improve participants' gambling criterion setting (willingness to gamble).

Feedback in Recognition Memory and Formula-Scoring Domains

The impact of feedback on the strategic regulation of accuracy has not been explored to date in a gambling domain. However, research over the last few decades has intermittently investigated the effects of corrective feedback in the field of recognition memory. Most research regarding feedback has focused on shifts in response bias (e.g., Azimian-Faridani & Wilding, 2006; Estes & Maddox, 1995; Rhodes & Jacoby, 2007; Van Zandt, 2000; Verde & Rotello, 2007). For instance, Rhodes and Jacoby (2007) explored criterion shifts with the manipulation of recognition item probability (base rates) of word location. Different screen locations were paired with different target probabilities. For instance, words that were presented on one side of a screen were typically old and words presented on the other side of the screen were typically new. The overall probability of old words presented during the test phase accounted for either 67% or 33% of the word lists at test. The results demonstrated that participants were able to shift their response criterion on an item-by-item basis, with participants adopting different criteria for the locations, and the shifts were more dramatic if participants were aware of the basis for doing so. In Experiment 3, trial-by-trial feedback resulted in a more liberal response criterion for predominately old versus new items, but this effect was significantly weakened when the feedback was removed, even when feedback was present in the first two blocks of trials but absent in the final two blocks of trials. Similarly, Dobbins and Kroll (2005) intermixed familiar photographs from the participants' campus with unfamiliar locations and found that criterion shifts occurred within lists, but this effect disappeared when participants were forced to respond rapidly, or with a one-week delay between study and test.

Previous research has concluded that participants were unwilling to shift response criterion once testing begins (e.g., Higham, Perfect & Bruno, 2009; Morell, Gaitan & Wixted, 2002; Stretch & Wixted, 1998), but it appears that the differing feedback instructions and stimuli used in the experiments lead to inconsistent findings regarding the role of feedback. Rhodes and Jacoby (2007) proposed that feedback may emphasise underlying base rates to participants, but participants find it difficult to explicitly attend to this information when feedback is absent. Han and Dobbins (2008) suggested that in their experiments, which used a biased-feedback approach (in which some decision errors were counted as correct), it is possible that feedback facilitates implicit response reinforcement learning. However, Han and Dobbins stated that further research was required in order to determine whether this was the case.

Likewise, Verde and Rotello (2007) investigated the role of memory strength on response criterion by varying the number of times items were studied. The researchers found that strength cues influenced initial criterion setting but participants were reluctant to shift their criterion after the initial placement. However, the accuracy feedback presented in Experiment 5 produced dynamic shifts in criterion. Verde and Rotello posit that 'people most likely respond not to the identity of the cues per se, but, rather, to some underlying stimulus property that the cues reveal... and discriminability may be the underlying property reflected by indirect cues' (p. 261).

More recently, however, research on strength-based within-list criterion shifts has found that people do shift their criterion on a trial-by trial basis without the need for feedback. For example, Bruno, Higham and Perfect (2009) explored a strength-based mirror effect within lists to determine which factors affected the response criterion. The mirror effect is a regularity that occurs in recognition memory contexts in which a manipulation (such as a strength manipulation of old/new words) simultaneously improves the hit rate (HR) and reduced the false alarm rate (FAR) in the better discriminated class of items or in the strongest encoded test lists (.g., Dobbins & Kroll, 2005; Glanzer, Adams, Iverson & Kim, 1993). Mirror effects are observed regularly when strength is manipulated between lists, for instance, when items are studied once versus three times in separate lists, but is rarely detected within lists. In Bruno et al.'s (2009) Experiment 2, participants were required to study a series of real words and non-words that were presented once or three times during study (depending on the randomly allocated condition). Study items (mainly non-words) were printed in capitals, however at test, half the participants viewed the strong targets and distractors in italics and weak targets and distractors were underlined (and vice versa for the other half of participants). A within-list mirror effect was observed when participants were made aware of the association between the perceptual cue and strength at test; hence, participants were able to effectively shift their response strategy depending on the number of times it had been presented. Experiment 3 detected a criterion shift for words studied for 0.5 seconds (low subjective memorability) but no shift was observed for words studied for 3.0 seconds (high subjective memorability). The researchers assert that response criterion shifts within lists relies on the extent that the participants attend to and use the test cues that designate strength (e.g., perceptual cues, as in Experiment 2, described above, or semantic categories, such as many items relating to body parts), only when the subjective memorability of the learning context is low.

Singer (2009) also demonstrated within list criterion shifts in experiments of delay-based strength manipulations. When participants were required to make semantic rating about each stimulus word, within list criterion shifts occurred when all study words in one category were presented consecutively (Experiment 1) and intermixed (Experiment 2). Further, in Experiment 3, within list shifts occurred only in the semantic processing condition, not the rote memorisation condition. Singer proposed three competing explanations of the within list criterion shift findings, which included the 'multirepresentational hypothesis', whereby rote learning yields surface representations, but semantic rating during learning produces both surface and more meaningful representations and the explanation put forward by Bruno et al. (2009). However, Singer stated that the explanations are areas for future investigations.

Moreover, very few studies have demonstrated enhanced sensitivity (discriminability) as a result of feedback. Whilst Gardner, Sandoval and Reyes (1986) found that old/new discrimination had improved after feedback in a recognition task, Kantner and Lindsay (2010) argued that Gardner et al. presented participants with the same test lists so participants in their study would naturally learn the correct responses to repeated items. Kantner and Lindsay used study lists to determine whether trial-by-trial corrective feedback could enhance the sensitivity of old/new items in a recognition memory task. In Experiment 2, participants were allocated to different base-rate conditions in which the old versus new items were manipulated; with a .75 (or .25) proportion of old items. During the study phase, participants were required to study a series of words that they were asked to remember for a later memory test. The test phase gave trial-by-trial feedback along with different audio tones for correct and incorrect responses. Participants had 1 point gained or deducted for each correct or incorrect decision, respectively, with point totals displayed quarterly throughout the test phase. The researchers found that feedback aided participants in moderating their response criterion; however, it had no impact on recognition sensitivity. This research supports the results of other studies that focus on uneven base-rate manipulation feedback (e.g., Estes & Maddox, 1995). Across four experiments conducted by Kantner and Lindsay, including the manipulations of deep/shallow processing and false-memory, feedback failed to enhance sensitivity, and accuracy was no higher for the feedback group than the control group.

In contrast, in Rhode's and Jacoby's (2007) Experiment 3, sensitivity was better for participants given feedback (a running point total) in the first two blocks compared to the participants given feedback in the last two blocks. Therefore, the timing of feedback (in terms of block presentation) may be an important factor to consider in improving sensitivity.

The abovementioned research has explored the role of feedback in type-1 contexts (stimulus-contingent). Research in the area of formula-scored testing has looked at the role of feedback in type-2 contexts (response-contingent), which is much more applicable to the current thesis for reasons explained in Chapter 1. Higham & Arnold (2007a) gave undergraduate students three four-choice alternative multiple-choice tests to determine whether students were able to learn from feedback. On each of the tests, participants were required to select the answer they believed was correct and indicate how confident they were in the accuracy of their answer. Participants were also required to designate the response to either a 'answer' column, in which participants would gain 1 point for a H or lose .50 point (Test 1) or .25 point (Tests 2 & 3) for a FA, or a 'guess' column, in which participants would gain .25 point for a M and would not lose anything for a CR. Feedback relating to the correct answers for each question were given in class. The findings showed that participants were generally too conservative in their responding across all three tests, and allocated too many answers to the guess category. Students did not appear to shift their response bias as a result of the feedback. Similarly, Higham (2007) gave trial-by-trial feedback in a formula-scoring scenario that did not alter decision performance. Higham and Arnold (2007a) also found that participants held stable accuracy and resolution (monitoring) scores. This research provides further evidence that feedback does not have an impact on resolution or accuracy, and perhaps in a type-2 context, response bias is difficult to shift. However, the reward given for a correct response in the 'guess' category (a M) could have led to the conservatism observed, and may have contributed to the resistance to shift criterion.

More recently, Arnold, Higham & Martin-Luengo (under review) explored the role of bias training in general knowledge tests. In a similar research design to the Higham and Arnold's (2007a) paper described above, participants were required to answer the questions by assigning responses to a 'go for points' or 'guess' column. In Experiment 3, participants were randomly allocated to either an educated group (who received optimal bias feedback, that is, how often they should be assigning responses to the guess category) or a control group (who received no feedback). Participants completed three general knowledge tests on paper to determine whether optimal bias feedback (feedback relating to the optimal number of responses that should have been assigned to the guess category) would be applied to a subsequent general knowledge test. A point structure was incorporated into the design, with 1 point gained for a H and .33 point lost for a FA. No points were gained or deducted if participants assigned a response to the guess category (Ms and CRs). The educated group received optimal bias feedback from the experimenter, which pertained to the optimal number of questions of which they should select the 'guess' option. Participants were told this feedback after the first and second tests and were required to go back over their responses and redistribute their 'go for points' and 'guess' responses to a more optimal level, before starting the next test. The findings showed that the optimal bias training on one test improved criterion-setting performance on a subsequent test for the educated group, and this beneficial effect of feedback lasted for tests 2 and 3, although participants in the educated group did not have a score advantage over the control group on test 3. Hence, optimal bias feedback has the potential to alter students' test-taking strategies. A criticism of this study was that the educated group were not allowed to move onto the next test until they had reached optimal bias. This type of training may have been confusing and counterintuitive for the participants because they may struggle to understand why some answers should be assigned to the 'go for points column' when they have very little confidence in their accuracy. Consequently, some incorrect answers were assigned to the 'go for points' column. Furthermore, resolution (that Arnold et al., under review) term metacognitive monitoring) remained stable across the tests, despite the feedback. This finding suggests that resolution (in type-2 contexts) and sensitivity (in type-1 contexts) are stable and difficult to improve using trial-by-trial feedback.

Previous experiments in this thesis (Experiments 2 – 6) have demonstrated an adaptive criterion set by participants, as evidenced by the different gambling likelihoods for different sums of the dice task (see Individual Sum Plots). However, participants have deviated substantially from optimal gambling, particularly with the more probabilistic sums between 5 and 12, although the RGs have been closer to optimal bias. Is it possible to enhance participants' gambling by providing 'optimal gambling' feedback? Further, some previous experiments (e.g., Jennings & Jacoby, 2003; Higham & Arnold, 2007a) have lacked control groups so it has been difficult to judge how much improvement in criterion placement has been a result of feedback. The present experiment will incorporate three experimental groups (including a control group) so the impact of feedback on gambling decisions can be clearly identified.

Study Overview

By providing optimal gambling feedback on the dice task, the aim of the Experiment 7 was to explore whether training participants would improve performance on a subsequent dice task block. If so, would this benefit also be observed one week later? The second aim of the experiment was to examine whether the presentation of supplementary feedback on specific gambling responses would increase the accuracy and resolution of decisions. Experiment 7 was considered to be important, as previous research designs have not incorporated a training component that specifically seeks to train individuals to perform more optimally in a type-2 gambling task. Whilst some recognition research has manipulated base-rates, the responses in a gambling task are not due to the remembering of an individual (such as in recognition memory contexts), but are more probabilistic. In the light of the experiment, it was conjectured that feedback may play a distinctive role in this context and that findings could potentially contribute to treatment programmes related to problem gambling.

Participants were randomly allocated to either a *control* group, or one of two educated groups: an *optimal gambling* (OG) feedback group or an *optimal gambling plus history* (OGH) feedback group. All participants were administered a baseline block, feedback block and two outcome blocks (presented one week apart) of the dice task. Participants were required to gamble with ‘high wagers’ or ‘low wagers’ on the landing of the unique die (0/3 decision). Participants allocated to the control group did not experience any feedback during the course of the experiment. The OG group were given feedback relating to their optimal proportion of low wagers after the baseline block and at various intervals of the feedback block. The OGH group experienced the same optimal gambling feedback as the previous group, but also viewed their accuracy, responses to sums, and the correctness of these answers at intervals throughout the feedback block.

It was hypothesised that both the OG and OGH groups would shift their gambling criterion to a more optimal setting; however, participants who experienced the addition of the history of past sums feedback would also significantly improve their resolution and accuracy. It was hoped that the benefit of this feedback would be long lasting, up to a week later. Type-2 SDT was again used to analyse the data.

Method

Participants

Ninety-six undergraduate students (20 males, 76 females, *M* = 21.49 years, *SD* = 3.70) from the University of Southampton were recruited to participate in the study. Advertisements were placed around the University campus and on the School of Psychology's electronic study advertising system. Only non-gambling individuals were required for the study due to ethical concerns.

Participants were randomly allocated to one of three conditions of the experiment (see the 'Design and Materials' section for the description of each condition): a control condition (*n* = 30, *M* = 21 years, *SD* = 3.01); an optimal gambling feedback condition (*n* = 31, *M* = 22.32 years, *SD* = 5.19); and an optimal gambling feedback + history feedback condition (*n* = 34, *M* = 21.18, *SD* = 2.37). Participants were compensated with £7 or course credits. A £20 'jackpot' was also offered to the participant who achieved the highest number of points across all blocks of trials, to encourage more realistic gambling behaviour.

Materials and Procedure

Participants were tested individually in a quiet research laboratory at the School of Psychology, University of Southampton. Each participant signed a written informed consent form before participation. The dice task (as fully described in Chapter 3) was used in the study. Participants were required to make a 0/3 decision and then to gamble with 'high' or 'low' wagers on that decision. If a high wager was chosen, participants would gain 4 points for a correct decision but would lose 5 points for an incorrect decision. If a low wager was selected, participants would gain one point for a correct decision, but would lose the same amount for an incorrect decision. The wager structures were chosen based on hypothetical bias profiles and the payouts used in Experiment 6 of Chapter 5. A points box was visible at the top right of the screen so participants could track their gambling. Participants were presented with four blocks of the dice task. Each block began with 100 points and no points were carried over onto the next block of trials. 'Ding' and 'buzzer' sounds were also incorporated into the game when the participants selected the correct and incorrect decisions, respectively. All sums presented to participants were associated with the rolling of the three dice, as in the previous experiments (6 [standard die] X 6 [standard die] X 2 [unique die]). The blocks of trials conformed exactly to the expected frequencies[26]. However, participants were not told the number of trials they would be completing during each block. The dice task was presented on an Apple Mac computer and programmed using Revolution software.

Participants were randomly allocated to one of three conditions, in which feedback was manipulated: the control group, the (OG) group or the (OGH) group (see Figure 6.1 for an illustrative representation of the blocks of trials presented to each group). The study was split into two sessions, spaced one week apart. In the first session, participants were required to complete a demographics questionnaire and then participate in three blocks of the computerised dice task, lasting a total of 45-55 minutes. All groups of participants were presented with an initial block of 72 trials of the dice task (baseline block). The first feedback group (OG) and second feedback group (OGH) received optimal gambling feedback after the baseline block. Based on their gambling responses during the baseline block, the programme counted the frequency of each participant's Hs (high wagered correct responses), FAs (high wagered incorrect responses), Ms (low wagered correct responses) and CRs (low wagered incorrect responses) and calculated the actual proportion of low wagers that were selected during the baseline block:

Actual proportion of low wagers = (Ms+CRs)/(Hs+FAs+Ms+CRs)

The programme also calculated the proportion of trials in which participants *should have* selected the low wager option in order to optimise their score (optimal gambling; see Appendix A for the methodology behind bias profiles). The OG and OGH groups were given the following optimal gambling information, which was presented on screen for 30 seconds:

[26] This methodology is considered analogous to the expected frequencies of card games in casinos, such as blackjack. Theoretically, participants could count the frequency of each sum that appeared on screen which yielded a certain number of 0 and 3 trials. However, no participants appeared to be 'sum counting' (they all went straight into the task), participants experienced a different number of trials during the training phase, and, as will become apparent in the results, the cognitions and metacognitions remained very stable across the blocks for the control group.

You have been gambling ___% of the time with low wagers. To optimise your score in the next block of trials, please gamble ___% of the time with low wagers.

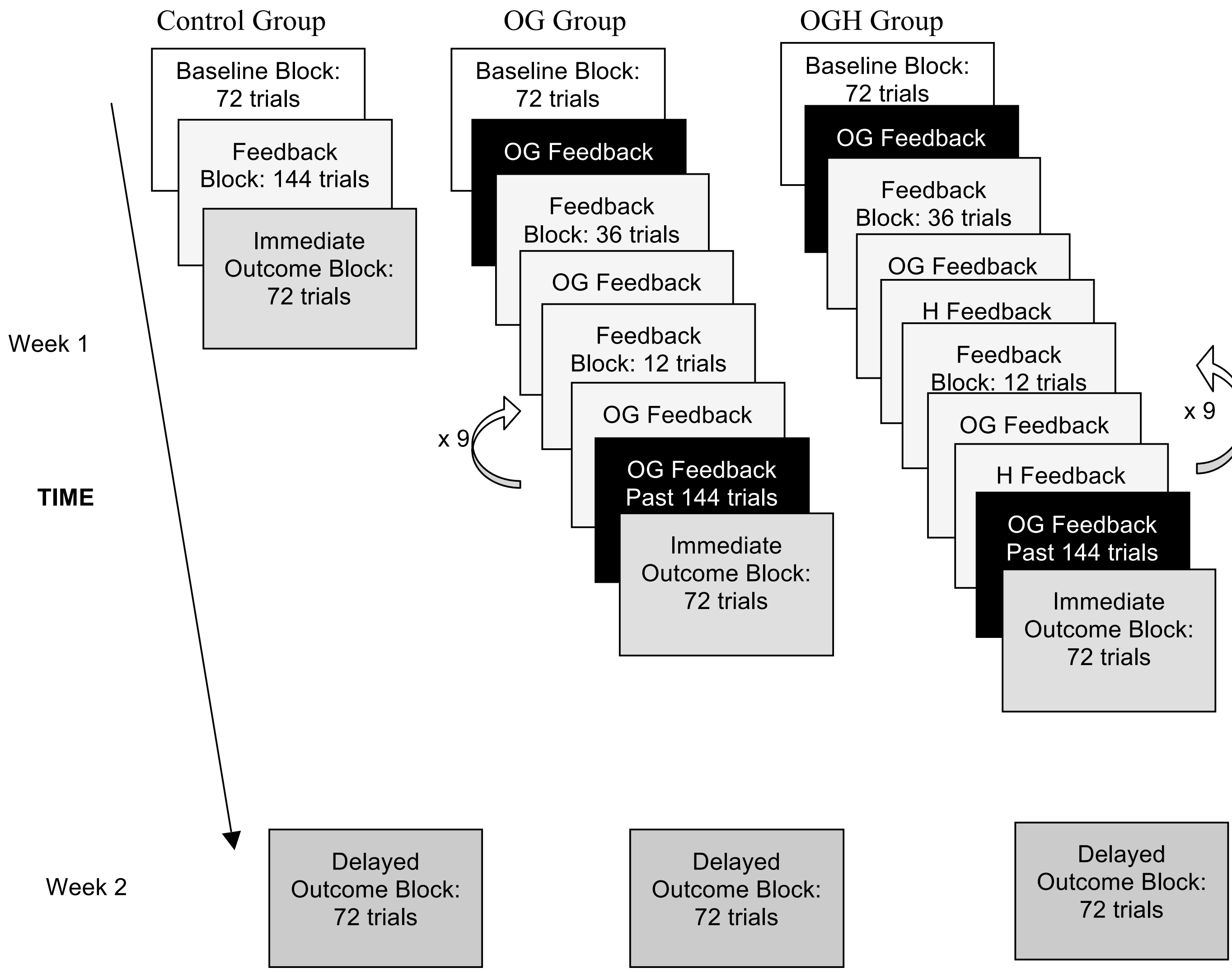

Figure 6.1. Schematic of the dice task presented to the three groups of Experiment 7. The blocks were self-paced; however, there was a two-minute break between each block of session 1, and the feedback was presented for a compulsory 30 seconds. OG = Optimal gambling; H = History.

After the optimal gambling feedback, participants were required to complete a 'pleasantness' rating of the optimal gambling feedback ('how pleasant was the feedback you just received?), ranging from 1 (not at all pleasant) to 7 (very pleasant). This rating scale was incorporated into the study design to encourage the groups to attend to the feedback on the previous screen.

The second block of trials (feedback block) incorporated 144 dice task trials (2 X 72 trials). A greater number of trials were presented in the training block so participants could not just copy the number of trials in which they selected low wagers on the subsequent outcome blocks. Optimal gambling was calculated for the OG and OHG groups after the first 36 trials and then every 12 trials, and presented to in the same format as above. It was anticipated that this frequent feedback would allow for participants to regularly reflect on the criterion they were currently adopting and to give them an indication of how liberally (or conservatively) they were gambling with low wagers. Hence, participants had the opportunity to alter their gambling over the subsequent trials. Optimal gambling was also calculated after the feedback block had been completed so participants could get an overall impression of how optimally they gambled throughout the entire block.

Along with the optimal gambling feedback, OGH also viewed 'history feedback' after the first 36 trials and after every subsequent 12 trials of the feedback block. History feedback involved a presentation of the sums from the past twelve trials, the correct responses, and their accuracy (see Figure 6.2 for the history feedback screen layout). This feedback was designed to be analogous to the history feedback that is often placed near a roulette table, detailing the previous reds and blacks in which the roulette ball has landed. The history feedback in the current study can potentially be very useful as the dice task is based on actual probabilities with some definitive answers (for instance, if the sum is 4, the unique die could only have landed on a 0), and so participants can learn from observing their past responses; unlike the history feedback at casinos where the red and black feedback of the roulette table are not indicative of future events (and can lead to the cognitive distortions of 'near misses' and the 'gambler's fallacy'). Therefore, by viewing the history feedback, participants can potentially increase both the accuracy and resolution of their decisions. The pleasantness rating was required after viewing the history feedback.

The third block of trials was an immediate outcome block and involved the presentation of 72 trials to all groups. These were the same 72 trials that were presented to participants during the baseline block, but presented in a random order. This block was designed to measure whether the feedback offered during the feedback block had an immediate impact on participants' gambling performance. No feedback was given during or after this block.

Please view your responses to the last 12 sums presented (oldest to the most recent one):

SUM	12	4	10	10	7	6	13	11	6	10	6	10
CORRECT DECISION	3	0	3	0	0	0	3	3	0	3	0	3
YOUR DECISION	✔	✔	✔	✗	✔	✔	✔	✔	✔	✔	✔	✗

Your decisions are 83.3 % correct in the last 12 trials.

Figure 6.2. The history feedback presented to participants in the OGH group.

Participants were required to book a second session for the following week in which a fourth block of 72 trials (delayed outcome block) was presented. The delayed outcome block was the same as the baseline and immediate outcome blocks, with the 72 trials randomly presented. This session was designed to measure whether the feedback had a lasting impact on the OG and OGH groups. Participants were reminded of the dice task and any questions were answered before beginning this block. Participants were not reminded of how they had gambled the previous week, and there was no mention of any feedback they received. This session was approximately 15-20 minutes. Participants received a debriefing form after the trials.

Experimental Design

The experiment used a 3 (group: control, OG, OGH) X 4 (block: baseline, feedback, immediate outcome, delayed outcome) mixed design, with between-participants on the former factor. Dependent variables included groups' accuracy, resolution and FARs.

Results

Accuracy Performance

The first analysis was a 4 (block: baseline, feedback, immediate outcome, delayed outcome) X 3 (group: control, OG, OGH) mixed ANOVA on accuracy, with group as the between-participants variable (see Table 6.1 for the means and SEs). The results demonstrated that the main effect of block was significant, $F(3, 276) = 3.01$, $MSE = .02$, $\eta_p^2 = .03$, $p = .03$, indicating that through practice on the dice task, participants significantly increased their accuracy. Post-hoc t-test comparisons (alpha = .016) confirmed that participants significantly increased their accuracy from the baseline block to the delayed outcome block ($t(94) = -2.62$, $p = .01$). The difference in accuracy from baseline to immediate outcome was approaching significance ($t(94) = -1.90$, $p = .06$), but the baseline block did not significantly differ from the feedback block. These results further demonstrate that practice on the dice task had a positive impact on accuracy performance the following week.

Table 6.1

Accuracy Performance as a Function of Block Presentation in Each Group of Experiment 7.

	Groups		
Block	OG	OGH	Control
Baseline	.66 (.02)	.65 (.02)	.67 (.02)
Feedback	.68 (.01)	.66 (.01)	.67 (.01)
Immediate Outcome	.68 (.01)	.67 (.01)	.67 (.01)
Delayed Outcome	.68 (.01)	.68 (.01)	.67 (.01)

Note. Standard errors of the mean are in parentheses. OG = Optimal Gambling Feedback Group; OGH = Optimal Gambling + History Feedback Group.

The main effect of group and the group by block interaction was not significant, largest $F(6, 276) = 1.09$, $p = .37$. This finding suggests that participants in the OGH group did not significantly benefit from the individual sum history feedback in terms of improving their accuracy. However, the means in Table 6.1 display a trend whereby the OGH's accuracy has increased from 65% to 68% from the baseline to delayed outcome blocks. It also appears that the OG group benefitted from the optimal gambling feedback (with an increase from 66% to 68% accuracy). The control group displayed very steady accuracy across all blocks, which invalidates the idea that practice has a beneficial effect on accuracy in the dice task.

Resolution Performance

Receiver Operating Characteristics (ROCs) were created by plotting the HRs and FARs for each confidence rating (1-6). The area under the curve (AUC) was then calculated by the trapezoidal rule (Pollack & Hsieh, 1969; see Table 1.2 for the AUC formula and Table 6.2 for the AUC means and SEs) to determine each group's resolution ability. AUC is an unbiased measure of resolution and avoids the difficulty in measuring d' when the HRs or FARs are undefined, and it uses the full ROC, rather than being based on a single point. AUC is equal to 0.5 for chance performance and 1.0 for perfect performance.

A 4 (block: baseline, feedback, immediate outcome, delayed outcome) X 3 (group: OG, OGH, control) mixed ANOVA on AUC was conducted, with group as the between-participants variable. Resolution remained stable across all blocks for all groups. The main effects of block and group, and the group by block interaction were not significant, largest $F(2, 92) = 1.56$, $p = .22$).

Table 6.2
Resolution Performance (AUC) as a Function of Block Presentation in Each Group of Experiment 7.

	Groups		
Block	OG	OGH	Control
Baseline	.60 (.01)	.61 (.01)	.61 (.01)
Feedback	.61 (.01)	.62 (.01)	.62 (.01)
Immediate Outcome	.62 (.01)	.60 (.01)	.64 (.01)
Delayed Outcome	.59 (.01)	.60 (.01)	.63 (.01)

Note. Standard errors of the mean are in parentheses. OG = Optimal Gambling Feedback Group; OGH = Optimal Gambling + History Feedback Group.

High-Wager Likelihood[27] Performance

The most important outcome to be gained from this study was determining whether participants could shift their gambling criterion to a more optimal position as a result of the feedback. Therefore, a 4 (block: baseline, feedback, immediate outcome, delayed outcome) X 3 (group: OG, OGH, control) mixed ANOVA on high-wager likelihood was conducted, with group as the between-participants variable. HWL is the proportion of high-wager gambles. The formula to calculate HWL is similar to the formula for GL, but as the present experiment uses a high-wager/low-wager decision option, rather than the gamble/guess option that was utilised in Experiments 1 to 5 of this thesis, the HWL can be calculated as follows:

$$\text{HWL} = \text{high-wagers}/(\text{high-wagers} + \text{low-wagers})$$

The mean HWLs per group can be viewed in Table 6.3. The main effect of block was significant $F(3, 276) = 12.72$, $MSE = .02$, $\eta_p^2 = .12$, $p < .001$, and indicated that participants gambled with significantly greater HWLs in the feedback ($M = .62$, $SEM = .02$), immediate outcome ($M = .65$, $SEM = .03$) and delayed outcome ($M = .64$, $SEM = .03$) blocks compared to baseline (all $ts(97) \geq -3.94$, $ps < .001$). The feedback, immediate outcome and delayed outcome HWLs did not differ from one another, although the difference between the feedback and immediate outcome HWLs was approaching significance, $t(94) = -1.93$, $p = .06$.

The analysis further revealed a significant main effect of group, $F(2, 92) = 4.17$, $MSE = .19$, $\eta_p^2 = .08$, $p = .02$. Post-hoc comparisons with Bonferroni correction (alpha = 0.02) demonstrated that the control group ($M = .52$, $SEM = .04$) gambled with significantly fewer high-wagers than the OGH group ($M = .67$, $SEM = .04$; $t(62) = -2.62$, $p = .01$). The difference between the controls and the OG group ($M = .65$, $SEM = .04$) was approaching significance ($t(59) = -2.24$, $p = .03$). The OG and OGH groups did not differ significantly ($t(63) = -.36$, $p = .72$). Generally, participants in

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[27] FARs were also analysed as the previous chapter highlighted the potential difficulty with using gambling likelihoods as a measure of gambling bias. The 3 (group: OG, OGH, control) X 4 (block: baseline, feedback, immediate outcome, delayed outcome) mixed ANOVA on FAR yielded significant main effects of block and group, $F(3, 276) = 9.39$, $MSE = .03$, $\eta_p^2 = .09$, $p < .001$, $F(2, 92) = 5.03$, $MSE = .25$, $\eta_p^2 = .10$, $p = .01$, respectively. The block by group interaction was also significant, $F(6, 276) = 5.85$, $MSE = .03$, $\eta_p^2 = .11$, $p < .001$. These FAR findings mirror the HWL findings reported, and suggest that gambling likelihood/HWL is in fact a good measure of bias in the current experiment.

this task were gambling too conservatively, that is, they were gambling with a greater number of low wagers and missing out on points that potentially could have been won.

This finding is qualified by a significant group by block interaction, $F(6, 276) = 5.60$, $MSE = .02$, $\eta_p^2 = .11$, $p < .001$. Bonferroni t-test comparisons (alpha = .03) demonstrated that the HWL for the control group immediate and delayed outcome blocks did not differ significantly from baseline (both $ts(29) < -1.20$, $ps > .05$). However, for the OG (both $ts(30) > 2.31$, $ps < .03$) and OGH (both $ts(33) > -3.89$, $ps < .001$) groups, the immediate and delayed outcome blocks yielded a significant increase in HWL compared to the baseline block. These results show that the OG and OGH participants were increasing the proportion of high wager gambles as a result of the feedback. Importantly, the feedback also had a lasting effect, with no reduction in HWL from the immediate outcome and delayed outcome blocks for both of these groups (both $ts < -.95$, $ps > .05$).

Table 6.3

High Wager Likelihood as a Function of Block Presentation in Each Group of Experiment 7.

	Groups		
Block	OG	OGH	Control
Baseline	.55 (.04)	.52 (.04)	.54 (.04)
Feedback	.66 (.04)	.71 (.04)	.50 (.04)
Immediate Outcome	.71 (.05)	.71 (.05)	.53 (.05)
Delayed Outcome	.68 (.05)	.73 (.04)	.51 (.02)

Note. Standard errors of the mean are in parentheses. OG = Optimal Gambling Feedback Group; OGH = Optimal Gambling + History Feedback Group.

In order to resolve the appropriateness of the increase in gambling likelihoods (greater proportion of high wagers) by the OG and OGH groups, the signed deviation from group optimal HWL was calculated for each group in each block and plotted in Figure 6.3. A 3 (group: OG, OGH, control) X 4 (block: baseline, feedback, immediate outcome, delayed outcome) mixed ANOVA was conducted on signed deviation, with group as the between-participants variable. The analysis yielded a significant main effect of block, $F(3, 276) = 13.66$, $MSE = .02$, $\eta_p^2 = .13$, $p < .001$. Post-hoc comparisons with Bonferroni correction (alpha = .008) demonstrated that participants deviated further from optimal bias in the baseline block ($M = .32$, $SEM = .02$) compared to the feedback ($M = .23$, $SEM = .02$; $t(94) = 4.23$, $p < .001$), immediate outcome ($M = .21$, $SEM = .03$; $t(94) = 4.41$, $p < .001$) and delayed outcome ($M = .22$, $SEM = .03$; $t(94) = -4.22$, $p < .001$) blocks. The three latter blocks' signed deviations did not significantly differ from one another (all $ts(94)$ between .470 and 2.06, $ps > .04$).

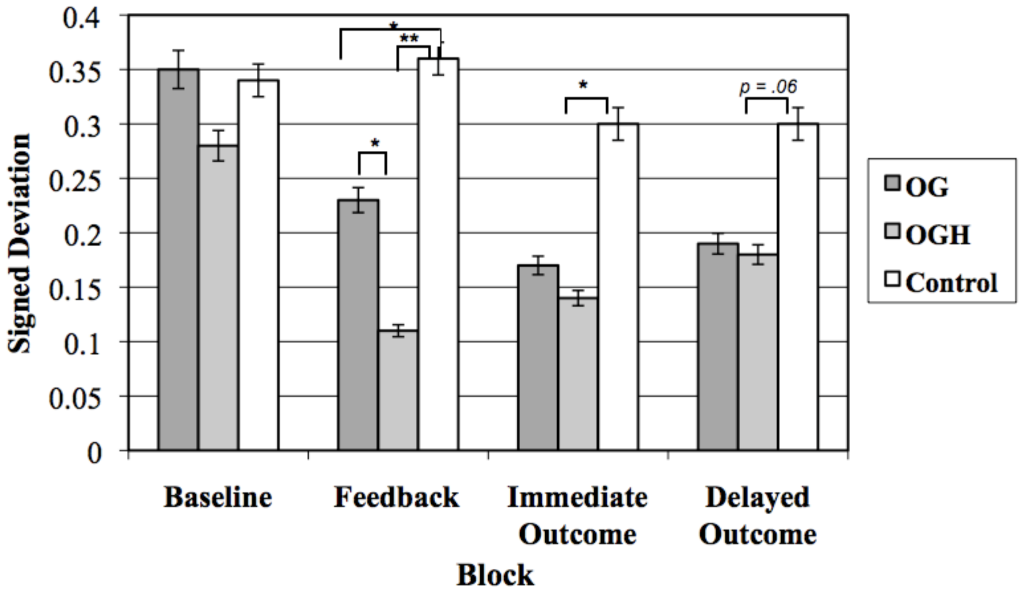

Figure 6.3. A graph to show the signed deviation from optimal high-wager likelihood for the OG, OGH and control groups across the blocks of Experiment 7. OG = optimal gambling feedback group; OGH = optimal gambling + history feedback group. * = $p < .05$; ** = $p < .001$.

The main effect of group was also significant, $F(2, 92) = 3.71$, $MSE = .19$, $\eta_p^2 = .08$, $p = .03$. The OGH group ($M = .18$, $SEM = .04$) was significantly closer to their optimal HWL compared to the control group ($M = .33$, $SEM = .04$), $t(62) = 2.64$, $p = .01$. Finally, the main effect was qualified by a block by group interaction, $F(6, 276) = 3.50$, $MSE = .03$, $\eta_p^2 = .07$, $p < .01$. This interaction came about because all groups were the same at baseline, but differences emerged in later blocks. As can be seen in Figure 6.3, the control group deviated furthest from optimal high-wager likelihood, followed by the OG group then the OGH group in this block. It appears that the additional history feedback information also had an effect on sensitivity to optimal high-wager likelihood, with participants in the OGH group gambling much closer to optimal bias than the OG group. The OGH group gambled significantly closer to optimal HWL in the immediate outcome block compared to the control group, and the difference was approaching significance one week later during the delayed outcome block. The optimal gambling feedback alone did not create as much sensitivity to optimal HWL as the optimal gambling plus history feedback.

Discussion

The present experiment investigated whether feedback on gambling performance could alter gambling strategy; and, if so, whether the modified behaviour was long lasting. Non-gambling individuals were recruited to participate in the study, and they were randomly allocated to either the control condition (who received no feedback) or one of two educated conditions, in which they received optimal gambling feedback (OG) or optimal gambling with history feedback (OGH).

The study found that the OG and OGH experimental groups significantly shifted their gambling criterion during the feedback block, and as a result, they gambled with a greater number of high wagers (a more optimal gambling strategy). Importantly, this criterion remained in place for the immediate outcome block and the delayed outcome block, which was completed one week later. This finding showed that participants had acquired a more appropriate gambling criterion during the feedback block and did not revert to their gambling criterion at baseline.

The history feedback that the OGH group observed did not appear to have a significant effect on the group's accuracy or monitoring rates, as hypothesised. It was evident that practice alone did not have an impact on accuracy or resolution performance, as demonstrated by the control group's performance. Accuracy and resolution also did not improve for participants in the educated groups, which suggests one of two possibilities: 1) that the feedback presented was not specific enough to promote change or improvement in these measures; or 2) that it is very difficult to improve the accuracy and resolution performance variables in this task as monitoring the sums (and the accuracy of the decision about the sums) is nearly impossible for sums in the middle range (sums of 8/9). The research outlined in the introduction also failed to detect improvements in discrimination (e.g., Arnold et al., under review; Kantner & Lindsay, 2008). However, Experiments 4-6 have highlighted significant accuracy and resolution differences between two populations.

Conceivably, more practice with the dice task, or gambling games in general (as per the RGs' performance) could result in greater accuracy and/or resolution improvements. As Arnold et al. (under review) suggested, future research should focus on distinguishing the types of feedback that improves discrimination versus criterion setting.

Most importantly, though, the additional history feedback meant that the OGH group not only shifted their gambling criterion, but also gambled more optimally than the control group at immediate outcome and delayed outcome. Perhaps the history feedback allowed participants to reflect more deeply on their past gambling responses, such as providing them with information about sums they should be selecting the high wager option, and which they should select the low wager option. The OG group did not view the history feedback so the optimal gambling feedback alone may have been ambiguous. That is, to inform individuals that they should be gambling a certain way (e.g., gamble with more high wagers) without an explanation as to *why* they should be gambling that way, is unlikely to have a lasting impact on modified gambling behaviour.

To explore whether the shift in gambling criterion would result in a better score for the OGs and OGHs, a 2 (block: immediate outcome, delayed outcome) X 3 (group: OG, OGH, control) mixed ANOVA on signed deviation from baseline score was conducted[28], with group as the between-participants variable. There was no main effect of block, or a block by group interaction, both $Fs < 1$. However, the main effect of group was borderline significant, $F(2, 92) = 3.01$, $MSE = 1864.87$, $\eta_p^2 = .06$, $p = .054$. Post-hoc t-test comparisons with Bonferroni correction (alpha = 0.02) indicated that the OG group deviated further from their baseline scores in the immediate, $t(59) = -2.09$, $p = .04$, and delayed, $t(59) = -1.95$, $p = .06$, outcome blocks compared to the control group, although these findings are only approaching significance due to the Bonferroni correction (see Table 6.4 for total scores achieved by each group across the four blocks presented, and signed deviation from baseline scores). A similar trend was also found for the OGH group compared to the controls, but to a lesser extent (immediate outcome deviation from baseline: $t(62) = -1.78$, $p = .08$; delayed

[28] A 4 (block) X 3(group) mixed ANOVA on the raw scores, with group as the only between-participant variable was also conducted. Whilst the analysis yielded a main effect of block, $F(3, 276) = 139.28$, $MSE = 848.97$, $\eta_p^2 = .60$, $p < .001$, there was no main effect of group or a group by block interaction, largest $F(6,276) = 1.05$, $p = .39$.

outcome: $t(62) = -1.63$, $p = .10$). The OG and OGH groups' deviations did not differ from one another (both $ts(63) < 1$).

Table 6.4

Total Scores and Deviation from Baseline Scores for Each Group of Experiment 7.

		Block			
Groups	Measure	Baseline	Feedback	Immediate Outcome	Delayed Outcome
OG	Score	162.06 (8.14)	252.39 (12.34)	183.00 (5.95)	182.87 (6.00)
	Deviation[a]			20.94 (5.99)	20.81 (6.12)
OGH	Score	159.91 (7.78)	240.21 (11.78)	177.26 (5.68)	178.71 (5.72)
	Deviation			17.35 (5.72)	18.79 (5.84)
Control	Score	168.57 (8.23)	235.40 (12.55)	170.87 (6.05)	172.40 (160.30)
	Deviation			2.30 (6.09)	3.83 (6.22)

Note. Standard errors of the mean are in parentheses. OG = Optimal Gambling Feedback Group; OGH = Optimal Gambling + History Feedback Group.

[a]This is the mean signed deviation from baseline score.

These findings suggest that the OG and OGH groups' shift in criterion to a greater number of high wagers resulted in higher scores than the controls. In relation to real world gambling, we might envisage a reduction in the amount of money lost, rather than an increase in the money or points won

Limitations of the Study

The study is not without limitations. The main limitation is that it did not include PGs. Non-gamblers were chosen to determine whether it was possible to modify gambling behaviour using an experimental approach before the paradigm is applied to a clinical population. An ethical concern is that this approach may encourage gambling behaviour rather than reduce it. Research to determine the motivations to gamble before and after an approach such as this would minimise this concern.

Another restriction of the study was that whilst the feedback was presented for a set time, the gambling trials were self-paced. Some research has shown that decisions made under time pressure, as opposed to self-paced, can alter underlying judgements, and time pressure has been shown to increase risky behaviour when the risk is high, and decrease risky behaviour when the risk is low (e.g., Dror, Busemeyer & Basola, 1999) so we might observe overly-liberal (for sums between 5 and 12) and overly-conservative (for sums 2-4 and 13-15) gambling, respectively, in the dice task with time constraints. As games in gambling venues often incorporate time pressures, for instance, the roll of the roulette ball and pressure from the croupier, the dice feedback task may lack some ecological validity. However, it is expected that any feedback approach that attempts to modify gambling behaviour would require more reflection time so that individuals can gain a greater understanding of how their cognitions relate to their behaviour. Again, further research is a requisite to determine the differences in behaviour observed through time-pressured gambling on this task.

Summary

Overall, the results of this experiment must be interpreted with caution. However, the preliminary findings do support three contentions with regard to gambling behaviour. An overriding conclusion is that immediate and regular feedback on gambling performance can impact on an individual's approach to gambling. Framed more specifically, as a consequence of this feedback, individuals can learn to shift their gambling criterion to a more optimal setting. Moreover, they can learn to adjust their approach to gambling and perform more optimally when they have the opportunity to reflect on where they have been gambling incorrectly. Furthermore, as postulated, this feedback can have a lasting impact up to one week later, and likely longer depending on the intensity and regularity of the feedback. There is no question that more research to explore the longevity of this modified gambling behaviour, and to determine the extent to which this feedback can be shifted successfully with regard to gambling criteria in problem gamblers, is required. The outcomes of the experiment – especially if validated or confirmed through future research – may be helpful in formulating treatment plans alongside metacognitive therapy or CBT, to give a measureable outcome in problem gamblers' modified cognition.

CHAPTER 7
GENERAL DISCUSSION

Partially triggered by easy access to online websites and national lotteries, evidence suggests that gambling as a form of 'social entertainment' is increasing globally. As there tends to be a correlation between the number of people who gamble and those who become problem gamblers, pressure to label problem gambling as an addiction, rather than an impulse disorder, has been growing. However, the cognitive gambling literature on this issue has been generally restricted to exploring the cognitive biases and irrational beliefs of social and problem gamblers. Whilst this research has been informative in identifying differences between the groups, it fails to provide an adequate explanation or to identify cause and effect as to the development of problem gambling.

The present research attempted to address the knowledge gap between what is known about those who gamble generally and those who gamble problematically, by focusing on metacognition, which can be analysed using a type-2 signal detection framework. Recent research has only just begun to apply type-2 SDT to the gambling domain (e.g., Dienes & Seth, 2009; Fleming & Dolan, 2010; Lueddeke & Higham, 2011; Persaud et al., 2007), but to date this research has not explored how this framework can be used to establish differences between gambling and non-gambling populations.

Two main aims guided the present research: first, that the application of type-2 SDT might help to inform our understanding of the cognitions and metacognitions of those who gamble non-problematically and those who develop behaviours associated with problem gambling; and, secondly, that research findings might provide insight into potential treatment interventions for this disorder. The thesis presents seven experimental studies driven by four specific research questions that were identified in the Introductory chapter. I will address each question during this chapter, before discussing the implications of my research and recommending future research avenues.

Are there substantial cognitive and metacognitive differences between problem, non-problem and non-gamblers, and, if so, what are these components?

The data from several experiments reported in this thesis provide evidence for substantive cognitive and metacognitive differences between groups of individuals on gambling task trials. Findings from Experiments 3, 4, 5 and the dice task of Experiment 6 support the development of a type of ‘gambling expertise’ in non-problem gamblers (RGs). Results suggest that the RGs are able to transfer to the novel dice gambling task what they have learnt about probabilities (in terms of accuracy of probabilistic decisions) and gambling criterion setting in their regular experience with other gambling tasks. Specifically, the RGs demonstrated significantly better accuracy of the 0/3 decision and they set more optimal criteria than the NGs and PGs in the manipulation of rewards and penalties when given a ‘gamble’ or ‘guess’ option, and in the manipulation of wager structures when given a ‘high wager’ or ‘low wager’ gamble option.

To illustrate, the PGs had regular exposure to gambling prior to the study (at least once a month), and similar educational attainment and age of first introduction to gambling as the RGs; however, Experiment 6 demonstrated the PGs’ significantly worse accuracy and criterion setting in the dice task. Essentially, the PGs exhibited similar gambling performance to the NGs, who also performed significantly worse than the RGs in Experiments 3, 4 and 5. Thus, the PGs appear to gamble as though they have never gambled previously. These findings further suggest that the PGs are impaired in learning from their gambling experiences, in contrast to the RGs.

The resolution findings across the experiments reported in this thesis were somewhat inconsistent, and it is difficult to determine whether there are distinct differences in resolution between the three groups studied. Yet, the inconsistencies can perhaps be partially explained by the nature of the tasks. The blackjack task of Experiment 1 was analogous to the first round of a blackjack game played in a gambling venue. Significant resolution differences were observed between the RGs and NGs in this task, with the RGs demonstrating better resolution performance than the NGs. This finding suggests that previous non-problematic gambling experiences result in better discrimination of correct and incorrect decisions, which may be considered an aspect of the development of gambling expertise. However, it is almost impossible to determine which previous gambling experiences accounted for the better resolution - whether it was previous experience specifically with the game of blackjack, or more general experience with different gambling games, as the RGs gambled on a range of gambling activities (both skill- and chance-based games) in their spare time.

In contrast, no significant resolution differences between the RGs and NGs were detected in Experiments 2-5. The findings suggest that gambling resolution may be game-specific, in that resolution may only improve on a gambling task after a certain amount of practice. Alternatively, resolution may be a much more difficult gambling skill to transfer compared to criterion setting or accuracy. Research discussed in Chapter 6 has shown that resolution, or sensitivity (in type-1 tasks), is a difficult component to improve in recognition and general knowledge contexts (Arnold, Higham & Martin-Luengo, under review; Kantner & Lindsay, 2010). Therefore, it may be no surprise that resolution is *almost* impossible to improve upon when the decisions integrate an element of chance, or are almost at chance level (e.g., 56% likelihood of a ‘0’ on the unique die when the sum of 8 is presented).

However, the RGs demonstrated significantly greater resolution than the PGs in the wager dice task of Experiment 6, which suggests that it is possible to improve gambling resolution, particularly as the likelihood of the unique die is nearer to definitive. In contrast, in the general knowledge task of Experiment 6, there no substantial resolution differences between the RGs and PGs. These findings highlight that different gambling games may result in varying underlying cognitive and metacognitive mechanisms between subtypes of gamblers and non-gamblers (e.g., Myrseth, Brunbour & Eidem, 2010; Toneatto, Blitz-Miller, Calderwood, Dragonetti & Tsanos, 1997). Nevertheless, the findings from the experiments reported in this thesis suggest that differences in accuracy and in the optimality of criterion placement are the mechanisms that most distinguishes regular, non-problematic gamblers from other types of players.

Does previous experience with gambling impact on cognitive and metacognitive variation?

Evidence from those who participated in the experiments suggests that previous experience with gambling can result in more refined gambling decisions in terms of higher accuracy and optimality of gambling criteria (Experiments 3-6), and in some instances, better resolution (Experiments 1 and the dice task of Experiment 6). Experiment 1 yielded differences in resolution between RGs and NGs, which suggests that gambling experience results in better discrimination between correct and incorrect decisions. However, the groups did not demonstrate significant differences in accuracy or gambling criterion in this experiment, which is somewhat debatable given the findings from subsequent studies. The lack of substantial differences may be explained by the limitations of the experiment, including the simplicity of the task. Had the blackjack task incorporated more rounds, greater differences between the two groups may have been observed on these cognitive components. However, the blackjack task was abandoned after Experiment 1, with the need for a novel gambling task to study gambling behaviour without previous experience on a specific game being an uncontrolled variable.

Further, the findings from Experiments 3-5 support the notion that gambling expertise develops over time, with the RGs able to transfer their knowledge of probabilities and gambling criteria to a novel task. Specifically, the RGs demonstrated greater sensitivity to both the rewards and penalties and the changing probabilities of the 0/3 decision and they completed the tasks with greater accuracy and more optimal gambling criteria than the NGs. It appears that gambling expertise may develop in much the same way as other expertise for some individuals (e.g., 'practice makes perfect'), to enable RGs to generalise what they know about gambling in order to perform more optimally in a novel gambling task.

However, the degree of experience on gambling tasks does not always determine performance. Those who were classified as 'problem gamblers' and 'non-problem gamblers' on the SOGS had similar backgrounds (university population) and reported similar lengths of time gambling and age at first introduction to gambling. Yet, the PGs gambled less optimally (both tasks of Experiment 6) and exhibited lower resolution and accuracy than RGs (the dice task of Experiment 6 only), so it may perhaps be more about 'how' individuals play the game rather than simply believing that gambling skills improve through repetitive action. One possible explanation for this observation is that these individuals may have difficulty in learning from their experiences in gambling settings. Alternatively, they may hold a greater number of irrational beliefs which impacts on their level of gambling control and metacognition. There is a considerable positive correlation between irrational beliefs and severity of problematic gambling (e.g., Xian, Shah, Phillips, Scherrer, Volberg & Eisen, 2008; see also Chapter 1 for a full discussion on irrational beliefs and gambling). Further research investigating *how* the irrational beliefs interact with metacognitive and cognitive decision making, and to determine cause and effect, is evidently required. Further, whilst we can roughly estimate the gambling exposure of the RGs and PGs, it is difficult to determine exactly how much game-play each individual has experienced over their lifetime before participation, and whether the RGs' expertise developed as a culmination of many different gambling games, or specifically games with elements of skill, particularly as almost all gambling participants reported playing a mixture of both skill- and chance-based games. If anything, the PGs may have underestimated their extent of their gambling involvement.

Supporting the idea that it is what individuals do with the information and how they process it that distinguishes experts from novices in gambling, Yu (2010) conducted a study to explore the attentional processing biases of belief revision in knowledgeable and unknowledgeable poker players. Participants were required to observe two virtual poker players with differing profiles based on their individual expectations of a high-quality poker player. Participants rated nine items of information on how likely a high-quality player would exhibit each characteristic (e.g., 'he has more years of experience playing poker than his opponent'). For example, if one participant had given a high ranking to playing professionally, then one virtual player's profile was explicitly labelled 'professional' whilst the other was labelled 'amateur', leading to a significant distinction between the two virtual poker player profiles. The characteristics that the participant felt were indicative for high-quality playing (salient cues) was displayed on one profile whilst the other profile only included one medium ranked characteristic (peripheral cue), whose characteristics were given a lower rating. The task was designed so that actual performance of the poker task favoured the player that the participant expected to be worse. Participants placed wagers on which of the two players would win the next hand: either £10 on one player or £5 on each player if there was an equally likely chance of both winning. Final ratings of the nine items of information were collected from participants after eight hands had been played.

Yu found that knowledgeable participants reduced the importance of each characteristic (focal cue) in the face of disconfirming evidence, whereas the novice participants' did not alter their ratings so drastically. Perhaps more importantly, the knowledgeable participants also increased the importance of the peripheral cue (the medium rated characteristic) in the final ratings, which was not displayed by the unknowledgeable participants. Hence, the researcher concluded that knowledgeable participants consistently updated their knowledge, regularly adjusting their prior beliefs in the face of both confirming and disconfirming focal and peripheral cues. In contrast, the unknowledgeable participants appeared to learn from salient focal cues only and blocked peripheral cues in the environment, only taking account of information that confirmed their prior expectations. However, the wager data indicated that participants in both groups were highly sensitive to disconfirming evidence, which was reflected in the decreasing confidence in initial expectations (less likely to bet £10 on the 'better' player). On the one hand, it could be argued that the unknowledgeable participants were more likely to have forgotten their wager pattern when completing the final ratings, which led to the post-experiment characteristic ranking differences between the two groups, or on the other hand, this behaviour may have been outside of conscious awareness.

Alternatively, Pretz (2008) proposed that experts perform better on everyday problem solving compared to non-experts because experts approach problems more analytically. Two studies were conducted to determine the appropriateness of strategy choice in solving everyday practical problems for experienced (senior undergraduates/staff) and non-experienced (first-year undergraduates) students. In both experiments participants were randomly allocated to either the 'analysis' strategy condition, in which they received explicit instructions on how to analytically solve an everyday problem using logic and analysis; the 'intuitive' strategy condition, in which they were given instructions that encouraged the use of intuition in problem solving; or a control condition, in which participants were not given any instructions.

Interestingly, the study showed that one cognitive strategy was not more effective than the other. Instead, the findings established an interaction between level of experience and success of problem-solving strategy, with experienced participants more successful in solving everyday problems when using an analytical approach, and the less experienced participants more successful when using an intuitive approach. Pretz described his findings in relation to the dual process theory of cognition (also outlined in Chapter 2), and proposed that when the experienced participants rely on intuition they are distracted from the critical information that they would process if using a more logical strategy. In contrast, the inexperienced participants do not easily recognise the critical information when problem solving so an intuitive strategy is more suitable. However, there is very little evidence for these assumptions, and Pretz concluded that more research is required to confirm these explanations.

The experiments reported in this thesis offer an alternative explanation for the development of expertise in some individuals who gamble but is not apparent in others. In short, it is argued that non-experts fail to adequately update their experience between the two systems (analytical and experiential) because their metacognitive processes are not as refined. Researchers have proposed that metacognitive monitoring and control mediates the two systems (Amsel et al., 2008; Kirkpatrick & Epstein, 1992; Klaczynski, 2004, 2005), and some studies have proposed that metacognition is required to allow the analytic system to override the intuitive/experiential system, which is the automatic system that we rely on first when faced with a problem (Epstein, Pacini, Denes-Raj & Heier, 1996). Because the problem gamblers have demonstrated weaker performance on the resolution and control components than the non-problem gamblers in Experiment 6 (dice task), it may be hypothesised that the problem gambling participants rely too heavily on their intuition and are therefore unable to gamble more rationally because these metacognitive components are impaired or not developed, despite facing disconfirming analytic evidence. In contrast, the expert gamblers were more sensitive to new information (manipulations of penalties/rewards and changing sums of the three die) and it could be argued that because they have better resolution and control, they can dismiss or limit the influence of the intuitive system and rely more heavily on analytic processing.

Whilst the PGs and NGs set suboptimal gambling criteria in the experiments presented in this thesis, it may be noteworthy that very few RGs actually gambled at optimal criterion setting (although they were significantly closer to doing so). There are always going to be biases in thought which impact on individuals' decision making, particularly in a gambling context where decisions are based around chance, and this idea is supported by literature which states that non-problem gamblers also hold irrational beliefs (e.g., Moodie, 2007), but not as many as problem or pathological gamblers (e.g., Delfabbro, 2004; Ladouceur, 2004). Even the 'experts' (RGs) observed in the present studies were biased in some way (too conservative much of the time) and did not perform completely optimally. It is probable that their own prior beliefs, inferences and knowledge about gambling and probabilities are still weighed relatively heavily, or are difficult to gamble completely rationally when given a gambling task they have previously never played. For instance, Bilalić, McLeod and Gobet (2008) demonstrated that expert chess players focused their attention on features of a solution to a problem they had already thought of (confirmation bias; the tendency to favour information that confirms beliefs), despite reporting that having found one solution they would then search for a better one. The irrational beliefs associated with problem gambling may be a result of being unable to shift effectively between the experiential and the analytic systems, or the irrational beliefs may cause the impairments of metacognition.

The findings from the general knowledge task of Experiment 6 also support the idea that metacognitive monitoring is related to irrational beliefs and highlights the importance in the type of game that is played when measuring cognitive and metacognitive variation. As the general knowledge task was dissimilar to the games that are available in casinos (not number-related), it may be put forward that both the PGs and RGs had no experience with this type of task and so had nowhere to anchor their prior beliefs. Subsequently, they had to rely on their intuitive judgement system, which resulted in similar accuracy and resolution performances for the two groups. However, the PGs still demonstrated poor criterion placement so it may be resolution rather than metacognitive control that is related to irrational beliefs. It appears that when cognitive biases lean too strongly in one direction and are resistant to updating by *disconfirming* evidence, problems can develop for some individuals, which may be one of the many underlying factors that contribute to problem gambling. It is clear that the relationship between expertise, irrational beliefs, and metacognition is an area that requires future investigation.

Can individuals be trained to improve resolution, gambling criterion and accuracy? If so, could feedback and training impact on potential treatment interventions?

The results from Experiment 7 suggest that feedback can significantly improve gambling performance in terms of setting a more optimal gambling criterion. After the training session of optimal gambling feedback, OG and OGH participants were able to significantly increase the proportion of high wagers of which they were betting. When the optimal gambling feedback was coupled with the history feedback (OGH group), an opportunity to view and reflect on specific sums and their accuracy, the shift in gambling criterion was even more optimal and longer lasting. These results contrast with the feedback experiments of Higham and Arnold (2007a) and Higham (2007) in which trial-by-trial feedback had no impact on formula-scored test performance. However, the present feedback study also incorporated trial-by-trial feedback in the form of a points box at the top of the screen and sound feedback, so this feedback component with the inclusion of the feedback presented during the training phase may have had an additional or interactive effect.

It was anticipated that the addition of the history feedback to the optimal gambling feedback (OGH group) would result in improved accuracy and resolution in the outcome blocks. However, both these components did not improve more than the control or OG groups. Research presented in the introduction of Chapter 6 detailed the difficulty in improving individuals' discriminability (type-1; e.g., Kantner & Lindsay, 2010, type-2; e.g., Higham & Arnold. 2007a) as a result of feedback. It may be that these two aspects are generally more difficult to improve in a single training session. Resolution did not differ between the NGs and RGs in Experiments 2-5, so this component may be difficult to transfer to a novel task, particularly as the Experiment 1 and Experiment 6 (dice task) findings demonstrated resolution differences between groups. Conversely, the accuracy of gambling decisions may have more potential for improvement through training, as the RGs had reliably greater accuracy than the NGs in Experiments 3-5.

It is noteworthy that the history feedback further improved participants' gambling criterion setting, and it was proposed that this variance results from providing participants with the opportunity to view and reflect on their past responses, allowing them to learn when they should be gambling with high wagers and when they should not. These findings may have implications for the design of interventions related to problem gambling. As one example, when considering treatment plans, clinicians may find the integration of frequent, specific and regular feedback as a key component to lessen, ideally eliminate, the uncontrollable urge to gamble, the 'impaired control'. The idea of assisting individuals in the understanding of their gambling problems and the rationales of their gambling urges is, of course, the premise behind cognitive behavioural treatment of problem gambling. One central question that remains an area of further inquiry is whether we would observe similar shifts in gambling criterion for a problem gambling cohort. The participants who took part in Experiment 7 were non-gamblers and they were chosen as pilot participants to see whether their behaviour could change as a result of feedback, before applying the model to a problem gambling cohort. Overall, the participants were too conservative when gambling with high wagers; it was an 'unnatural' activity to gamble when they were not used to doing so, and they preferred to bet with lower stakes. Generalising the findings to PGs, it is conceivable and argued here that PGs could be trained or conditioned through feedback loops and self-correction to gamble in a way that they are resistant to, for instance, gambling with a much lower proportion of high wagers, or not gambling at all. Further, as highlighted in Chapter 5, the PGs involved in Experiment 6 had gambled regularly for several years and generally started gambling in their mid-adolescence (see Table 5.1 for specific demographics). Therefore, after years of gambling a certain way (e.g., with too many high-wagered bets, chasing of losses), it may be more difficult for the feedback to impact on the PGs' decision-making.

Extending the present feedback experiment to include PGs, and possibly demonstrating marked shifts in gambling criterion with this population, might also potentially offer another viable strategy to assist in treatment and relapse prevention. How individuals monitor and regulate their behaviour may be more significant than the content of the beliefs (Millar, 2003), and forms the basis of metacognitive therapy, discussed later.

To what extent does Type-2 Signal Detection Theory inform our understanding of gambling behaviour and contribute to the literature on gambling?

Type-2 signal detection theory is used to analyse data from experiments in which participants must discriminate between their correct and incorrect responses. In essence, the analysis quantifies metacognitive sensitivity. Thus, it is suitable for studying gambling behaviour in which individuals must self-assess the accuracy of their gambling decisions before deciding whether or not to gamble. Type-2 SDT was applied to the present data in each experiment to extrapolate three main cognitive and metacognitive mechanisms that underpin gambling behaviour in problem gamblers, non-problem gamblers, and non-gamblers. Group accuracy, resolution (metacognitive monitoring), and gambling criterion (control), along with each groups' optimality of decisions were analysed in order to gain further understanding of the cognitive differences, which may lead to the development of problem gambling in a small proportion of people who regularly gamble.

The response-contingent framework has previously been applied to the fields of memory and recognition research (e.g., Higham, Perfect & Bruno, 2009), and more recently, it has been utilised in gambling research to explore issues of conscious and unconscious awareness (e.g., Dienes & Seth, 2008; Kunimoto, Miller & Pashler, 2001; Persaud et al., 2007). Other research has focused on optimal criterion settings (e.g., Peterson & Beach, 1967). However, no one has explored type-2 SDT with both optimal criteria setting and gambling. Moreover, these are the first studies to explore gambling group differences using type-2 SDT.

Metacognition has been defined in various ways to describe the self-regulation of thoughts, feelings and behaviour, depending on the context (see Introduction for a full discussion). In psychology, two processes have been identified which characterise metacognition: metacognitive monitoring and metacognitive control (Koriat & Goldsmith, 1996; Higham, 2007). The value of type-2 SDT in this thesis is that it has allowed the separation of gambling response determinants into those that involve the self-assessment and discriminability of responses (resolution) and those that involve the willingness to gamble (bias/control). The model allows the conceptualisation and illustration (see Figure 1.2) of how decisions can be influenced by these two components, and more specifically to type-2 SDT, how confidence in decisions are related to resolution and criterion shifts, and the strategic regulation of accuracy.

However, it may be helpful to consider some limitations of applying type-2 SDT to gambling. The model as it stands requires responses in all four cells of the contingency table shown in Tables 1.1 and 2.1 in order to calculate the hit and false alarm rates, which in turn are used to calculate resolution and bias. Macmillan and Creelman (2005) stated that most experiments avoid complete chance and complete perfect performance; however, the researchers were referring to type-1 SDT, where there are a fixed number of experimenter-defined trials, so rates of 0 and 1 are unlikely. In contrast, with type-2 SDT, the number of correct and incorrect trials are defined by the participant, not the experimenter. Thus, if a participant's accuracy is very high or very low there will be few false alarms or hits, respectively, leading to an undefined *d'*. Similarly, the difficulty in measuring bias is that participants may be too extreme in setting their gambling or guessing criterion. In particular relation to gambling research, problem gambling is characterised by impaired control, therefore, there are likely going to be very few trials in which problem gambling participants select the 'guess' option[29].

[29] It may be argued that it is also difficult to study gambling cognitions and metacognitions with games of complete chance e.g., slot machines/roulette as type-2 SDT has only been applied to situations whereby there is some skill involved (dice task) or there are definitive

Macmillan and Creelman (2005) identified two adjustments to avoid infinite values of d' caused by hit and false alarm rates of 0 or 1: converting rates of 0 and 1 to $1/(2N)$ and $1-1/(2N)$, respectively (see also Fleming & Dolan, 2010), or adding 0.5 to all cells regardless of whether zeroes are present. Hautus (1995) showed that each correction introduces bias in the estimation of d', but the latter adjustment is less biased. An option to address this problem could be to separate the responses post-hoc into gambles with greater confidence versus gambles with lower confidence. However, then the resolution measure may be dependent on response bias, as greater confidences are associated with the gamble/high wager options and lower confidences are associated with the guess/low wager options. It is important to be able to measure the two mechanisms without the confounding influences of the other measures. It is noteworthy, though, that Galvin et al. (2003) proposed that type-2 discriminability can be strongly affected by both response bias and type-1 sensitivity, which raises further questions for future research.

An alternative to correcting HRs and FARs would be to utilise measures that do not rely on defined rates. To illustrate, AUC, was used as a measure of resolution in Chapter 6. AUC is derived from Receiver Operating Characteristic curves (ROC), can utilise all the data without having to make any adjustments, and so it is an unbiased measure of resolution that is independent of the criterion that an individual has set (Green, 1964; Norman, 1964). Pollack and Hseih (1969) suggested that AUC was a truly nonparametric measure and so even if the underlying distributions are not normal, the measure of resolution is not likely affected. Some researchers have, however, criticised this measure due to a difficulty in obtaining reliable and valid AUC estimates, and it may not correlate well with measures of d' (Lobo, Jiménez-Valverde, & Real, 2008; Hand, 2009). Masson and Rotello (2009) proposed that the area under the AUC curve has ‘low statistical bias, has low standard error, and is not affected by the standard deviation ratio of the underlying distributions’ (p. 518; see also Macmillan, Rotello & Miller, 2004).

Whilst d' is the most widely used measure of discriminability type-1 context (Macmillan and Creelman; 2005), the gamma coefficient (G), which was first

right and wrong answers (such as in general knowledge tasks or recognition memory). However, there will still be more advantageous ways of gambling on chance games, for example, selecting the ‘hold’ button on two slot machine cherries before spinning again. Potentially, SDT could be applied to these games as well to measure gambling performance.

advocated by Nelson (1984), has been much more commonly used to study metacognitive processes (type-2 contexts; e.g., Higham, Luna & Bloomfield, 2011; Kao, Davis & Gabrieli, 2005; Souchay, Isingrini, Clarys, Taconnat & Eustache, 2004). Nelson (1986) put forward that gamma could be used as a measure of discrimination accuracy because it did not rely on the distributional assumptions associated with SDT. However, gamma has recently come under attack by various researchers who have identified a number of problems with this measure. For instance, Masson and Rotello (2009) simulated recognition memory data and utilised real data to explore how *G* transformed based on a range of criterion values for equal and unequal Gaussian distributions and rectangular distributions. The results demonstrated that *G* is associated with a large sampling variability, high Type 1 error rates, and varies depending on the response bias (changes in false alarm rate; see also Rotello, Masson & Verde, 2008), and the researchers argue that *G,* much like other measures of discrimination (such as d'), depends on the underlying evidence distributions, which are often not taken into account. Masson and Rotello concluded their article with a recommendation that d_a, a generalisation of d' that is sensitive to variances of the underlying distributions, is a more 'robust' measure of discrimination that accounts for distribution changes and response bias (p. 523). Moreover, Maniscalco & Lau (2012) argued that previous methods of type-2 discriminability, such as gamma, the correlation coefficient phi (Kornell, Son & Terrace, 2007), and intuitive percent correct (Persaud et al., 2007), are at risk from interference from response criterion setting and type-1 task performance and may, therefore, not be a true measure of type-2 discriminability. Further research is needed to clarify which is the most reliable measure of resolution performance, as there is currently no consensus on the best measure.

Additionally, the criterion measure of *c* was replaced with gambling likelihood in Experiments 4, 5 and 7 (HWL), as an alternative measure of criterion setting. Gambling likelihood (GL) was chosen due to its intuitiveness; a gambler who gambles versus guesses a lot seems to have a very liberal gambling criterion. However, theoretically, GL can be affected by the other performance parameters of accuracy and resolution. Therefore, in Chapter 5 the FAR analysis (an alternative measure of response criterion; as used in Higham, Bruno & Perfect, 2010) was compared with the HWL[30] measure to determine whether HWL (or GL) was attributed to criterion shifts alone, or influenced by the other performance measures. The findings indicated that HWL appears to be a good measure of criterion setting, which is not influenced by accuracy or resolution, at least in the experiments presented in this thesis.

Type-2 SDT applied to gambling in the present thesis is founded on two main assumptions: that the underlying distributions are Gaussian, and that high confidences elicit gambling or high wager responses. Whilst Macmillan and Creelman (2005) recognise that there are many other types of threshold models, with various distributional assumptions, the researchers endorse Gaussian or logistic models. Further, a range of experiments on type-1 and type-2 SDT have been conducted in the areas of recognition memory, general knowledge and post-decision wagering which have successfully supported the assumptions associated with theoretical normal distributions (e.g., Fleming & Dolan, 2010; Higham, 2007; Singer, 2009). Bias profiles also share the same assumptions as SDT but it may be noteworthy to consider that PGs may actually have very skewed correct and incorrect distributions compared to RGs or NGs, particularly as PGs often show overconfidence in their decision-making, and therefore lower confidences also elicit gambling behaviour. Further research to determine participants' actual response distributions is clearly required, but non-parametric measures, such as AUC, are currently useful in distinguishing distinct differences between groups.

Despite the criticisms of SDT, Chapter 5 highlighted the effectiveness of the approach in establishing the mechanisms underlying the confidence-accuracy disassociation observed between the RGs and PGs. Further, optimal performance measures could be calculated in Experiments 2-7 to determine the optimality of gambling decisions. Specifically, it would have been difficult to analyse decisions under uncertainty and come to definitive conclusions without being able to take into account how well individuals discriminated between their correct and incorrect decisions. For instance, Persaud and colleagues (2007) contended that wagering was an objective measure of awareness in the Iowa Gambling Task, and they suggested

[30] Gambling likelihood in Experiment 6 (Chapter 5) corresponds to the proportion of 'high wager' gambles versus 'low wager' gambles, compared to the gambling likelihood measure in Experiments 4 and 5 (Chapter 4), which corresponds to the proportion of 'gamble' versus 'guess' responses.

that the probability of betting with high wagers on correct decisions is a worthy indication of an individual's good discrimination. However, the researchers failed to report how participants bet on incorrect decisions, which is required for an accurate reflection of individual's strategic regulation of accuracy, and would further confirm or disconfirm whether post-decision wagering is a suitable measure of awareness (see Dienes & Seth, 2009; Seth, 2007; and Konstantinidis & Shanks, 2011, for full discussions as to the relationship between post-decision wagering and awareness).

Broader Implications for the Treatment of Problem Gambling

Lambos and Delfabbro (2007) suggested in an experimental study that educating gamblers about the odds of gambling is an unlikely harm minimisation strategy or a way to reduce cognitive biases, so alternative methods of addressing irrational beliefs and impaired control are evidently required. Therefore, the understanding that metacognition is not just one construct- but two- could be potentially very useful for treatment programmes relating to problem gambling. Type-2 SDT would establish whether the individual has a specific impairment in resolution (discrimination between correct and incorrect decisions), control (criterion setting), or both, which would be difficult to measure using self-report questionnaires in common practice. Also, variation in impairments may have implications for different treatment methods; for example, a gambler with poor resolution and who demonstrates very poor criterion placement may need a longer treatment course than a gambler who is impaired on only one of these components. Thus, understanding exact underlying cognitive and metacognitive difficulties of gamblers could mean further individualised treatment. In this vein, depending on the outcomes of future studies, a gambling task that involves type-2 SDT analysis may potentially be used as a screening tool to not only identify if someone is a problem gambler, but also to classify the exact mechanisms of which they are impaired.

C*ontrolled gambling* has been accepted as a satisfactory treatment outcome (Dickerson & Weeks, 1979; O'Connor, Ashenden, Raven & Allsop, 2000), and outlines that PGs can learn to control their gambling so that they can still gamble with a limited number of bets and retain their enjoyment of gambling (as opposed to the abstinence approach of many other treatment interventions, such as Gambler's Anonymous). The effectiveness of cognitive and cognitive behavioural (CBT) treatments to problem/pathological gambling, which involves teaching strategies to understand and correct cognitive errors, has received little experimental attention. Whilst some research has shown positive results with complete abstinence or few relapses after treatment (Ladouceur et al., 2001; Sylvain, Ladouceur & Boisvert, 1997), most research reported has encompassed few control groups, small sample sizes and non-specific treatments for this client group (George & Murali, 2005). Orford (2003, p.226) states that “the problem-gambling treatment field is lagging 20 or 30 years or more”, borrowing models from the treatment of substance misuse, and although gambling is viewed by many as an ‘addiction’ it is still classified as an ‘impulse disorder’ (DSM-IV; American Psychiatric Association, 1994) and has different cognitive bases for continuing to gamble.

More recently, individual cognitive-behavioural models have been developed for problem gambling (Ladouceur, Sylvain, Boutin & Doucet, 2002; Petry, 2009), but research into the efficacy of cognitive and cognitive-behavioural interventions for people with gambling problems is still being explored.

Whereas CBT focuses on the meanings individuals give to their experiences, *Metacognitive Therapy* (MCT) proposes that it is how individuals deal with these meanings which results in inflexible or recurrent styles of thinking (negative feelings and beliefs) and maintains some disorders (Wells & Purdon, 1999). MCT was originally developed to treat mood disorders such as anxiety and depression by addressing unhelpful self-regulatory behaviours, rumination and fixed attention, although more recently the MCT model has been applied to post-traumatic stress disorder, smoking and alcohol dependence disorders (Spada, Nikcevic, Moneta & Wells, 2007; Spada & Wells, 2008). The methodology behind Experiment 7 can be applied to clinical practice. The optimal gambling feedback may be comparable to a behavioural approach whereby individuals are instructed to gamble a certain way (or to reduce the number of high or low wagers). However, the history feedback offers a metacognitive perspective, and together with the optimal gambling feedback, this may be analogous to a metacognitive behavioural therapy approach, which appears to be more effective than behavioural treatments alone (e.g., controlled gambling). The fundamental impairments a gambler exhibits determine the suitability of each intervention, but potentially CBT and MCT could be combined to address difficulties with irrational beliefs (CBT) and the monitoring/control of thoughts and behaviours (MCT). For instance, Todd & Wells (2009) combined the two therapies in a manual for the treatment of bulimia nervosa and binge eating.

Final Conclusions

The present research offers a distinctive contribution to the gambling literature by exploring gambling behaviour using a type-2 signal detection approach. Seven experimental studies were conducted to investigate cognitive and metacognitive differences between problem gamblers, non-problem gamblers and non-gamblers. Generally, the findings showed that the non-problem gamblers were sensitive to the demands of the gambling tasks and had greater accuracy and resolution performances, and set more optimal gambling criterion settings compared to the other two groups. The approach advances our knowledge of the aspects that are involved in the development and/or maintenance of problem gambling, as it allows the differentiation between components of cognition and metacognition, and assists in exploring the optimality of decisions for expert and non-expert gamblers.

Whilst the participants who took part in the experiments shared very similar backgrounds (mainly students/staff from university populations), the studies may be criticised in terms of gender differences between the different gambling populations. For instance, the majority of RGs/PGs in the studies were male, whereas the majority of NGs in the studies were female, and it may be suggested that this sampling bias may be a causal factor in any observed differences in the studies. However, in opposition of this view, participant backgrounds were matched as closely as possible (see Tables 4.1 and 5.1), with very few other background differences between the groups. If males are more impulsive, which has been shown to precede later gambling problems (e.g., Vitaro, Arseneault & Tremblay, 1997), and accounts for the findings, then the RGs (who consisted mainly of male participants) should have been gambling more impulsively in the experiments, but instead the RGs were much more strategic and could control their willingness to gamble much more effectively than the NGs (consisting mainly of female participants). Further, if the obtained results were a result of gender differences, then the RGs and PGs, with both groups consisting of approximately 70% males in Chapter 5, should be gambling very similarly, which again is not the case and distinct cognitive and metacognitive differences were evident.

It should, however, be noted that the results may be difficult to generalise to a wider gambling population: females may be drawn to gambling for very different reasons to men, and tend to play different types of games (Heater & Patton, 2006), and further research in determining different types of individuals who are attracted to gambling, and who gamble problematically, is required. Some researchers have started to subtype problem gamblers based on their psychopathology, maladaptive personality traits, and motivations (Blaszczynski & Nower, 2002; Milosevic & Ledgerwood, 2010). Three subtypes of gamblers have emerged from the literature: the individual who gambles to escape negative life events characterised by mood and anxiety disorders (Ledgerwood & Petry, 2006); the individual who is highly impulsive and gambles to decrease boredom; and the individual who gambles due to social influences and faulty cognitive processes (Turner, Jain, Spence & Zangeneh, 2008). Indeed, different subtypes of problem gamblers may also have varying impairments of cognition, and future empirical research should focus on these subtypes in relation to the development of expertise, irrational beliefs and dual process accounts of gambling, as mentioned previously in this chapter.

The prevention and harm minimisation of problem gambling, as opposed to treatment, is an area of recent interest, and there has been much debate surrounding the Gamcare proposals to introduce education on 'responsible gambling' during personal, social and health education classes in schools (Gamcare Annual Review, 2011). Gamcare, the leading provider of information, support and free counselling for the prevention and treatment of problem gambling, argues that children should be educated about the risks associated with gambling, in order to prevent the development of problem gambling. However, a similar initiative in Canada was judged as unsuccessful, which left students more aware of gambling without being able to identify the warning signs of problem gambling (Lemaire, de Lima & Patton, 2004). As there is a correlation between the introduction of gambling at an early age and problem gambling, with 2% of adolescents classified as problem gamblers (Gupta & Derevensky, 2000), clearly children need to be made aware of the risks of gambling, just as they are educated about the risks of drugs and alcohol. However, the best way to educate is still a topic of much further discussion and debate.

To conclude, ultimately, problem gambling is a multi-faceted and complex disorder. Whilst the research outlined in this thesis further enhances our understanding of both expertise with gambling and the components which distinguish problem and non-problem gamblers, a multi-disciplinary approach from other areas of psychology, neuroscience, genetics, sociology and anthropology (among other disciplines) is required in order to gain a fuller understanding of the factors that contribute to the development and maintenance of problem gambling. The present research holds the potential of not only informing and refining cognitive approaches to understanding problem gambling, but also helping to treat the deleterious consequences of such a harmful and negative disorder.

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APPENDIX A
COMPUTATION OF OPTIMAL BIAS AND MAXIMUM SCORE: METHODOLOGY BEHIND BIAS PROFILES

The optimal gambling likelihood (criterion) can be estimated from *bias profiles*, which are a plot of the gambling score as a function of the guessing rate (e.g., see Higham, 2007; Higham & Arnold, 2007a, 2007b). The gambling score (computed as if the game has only one trial) can be expressed as a function of overall accuracy (f), the HR and associated rewards for Hs (r), FAR and associated penalties for FAs (p), and *d′* (resolution measure):

$$\text{Gambling score} = r*HR*f - p*FAR*(1-f) \quad (1)$$

The H, FA, M and CR cells in Table 2.1 represent frequencies, but it is possible to calculate the probabilities of P(H), P(FA), P(M), P(CR):

$$P(H) = H/(H + FA + M + CR) = HR*f \quad (2)$$
$$P(FA) = FA/(H + FA + M + CR) = FAR*(1-f) \quad (3)$$
$$P(M) = M/(H + FA + M + CR) = f-P(H) \quad (4)$$
$$P(CR) = CR/(H + FA + M + CR) = (1-f)-P(FA) \quad (5)$$

It is now possible to express the probability of guesses as a function of HR, FAR, and f:

$$P(guess) = P(M) + P(CR) \quad (6)$$
$$P(guess) = (f - HR*f) + [(1 - f) - FAR*(1 - f)] \quad (7)$$
$$P(guess) = 1 - HR*f - FAR*(1 - f) \quad (8)$$

If one assumes an equal-variance Gaussian SDT model (e.g., Higham, 2007), the HR can be expressed as a function of FAR:

$$HR = \Phi(zFAR + d') \quad (9)$$

where $\Phi(x)$ refers to the probability under the standard normal distribution for a *z* score equal to x, and zFAR refers to the *z* score corresponding to FAR. This term can then be substituted for HR in equations 1 and 8:

$$\text{Gambling score} = r * \Phi(zFAR + d') * f - p * FAR * (1 - f) \tag{10}$$

$$P(\text{guess}) = 1 - \Phi(zFAR + d') * f - FAR * (1 - f) \tag{11}$$

With these substitutions, both the gambling score and P(guess) are expressed as a function of the FAR, resolution (*d'*), overall accuracy (*f*), the penalty for FAs (p), and the reward for Hs (r). For a given participant, *d', f, p,* and *r* will be fixed, and the FAR can be varied from 0 to 1, which will generate different values of the gambling score (Equation 10), and different values of P(guess) (Equation 11). It is then possible to plot corrected scores against corresponding P(guess) values (the bias profile) which will indicated the P(guess) value yielding the maximum gambling score: *optimal bias*.

APPENDIX B
HOSPITAL ANXIETY AND DEPRESSION SCALE (HADS)

Please read each item and indicate the response that comes closest to how you have been feeling in the past week. Don’t take too long over your replies; your immediate reaction to each item will probably be more accurate than a long thought-out response.

I feel tense or ‘wound up’:

☐ Most of the time
☐ A lot of the time
☐ From time to time, occasionally
☐ Not at all

I still enjoy the things I used to enjoy:

☐ Definitely as much
☐ Not quite so much
☐ Only a little
☐ Hardly at all

I get a sort of frightened feeling as if something awful is about to happen:

☐ Very definitely and quite badly
☐ Yes, but not too badly
☐ A little, but it doesn’t worry me
☐ Not at all

I can laugh and see the funny side of things:

☐ As much as I always could
☐ Not quite so much now
☐ Definitely not so much now
☐ Not at all

Worrying thoughts go through my mind

- ☐ A great deal of the time
- ☐ A lot of the time
- ☐ From time to time but not too often
- ☐ Only occasionally

I feel cheerful:

- ☐ Not at all
- ☐ Not often
- ☐ Sometimes
- ☐ Most of the time

I can sit at ease and relaxed:

- ☐ Definitely
- ☐ Usually
- ☐ Not often
- ☐ Not at all

I feel as if I am slowed down

- ☐ Nearly all the time
- ☐ Very often
- ☐ Sometimes
- ☐ Not at all

I get a sort of frightened feeling like 'butterflies' in the stomach:

Not at all

- ☐ Occasionally
- ☐ Quite often
- ☐ Very often

I have lost interest in my appearance:

- ☐ Definitely
- ☐ I don't take as much care as I should
- ☐ I may not take quite as much care
- ☐ I take just as much care as ever

I feel restless as if I have to be on the move:

- ☐ Very much indeed
- ☐ Quite a lot
- ☐ Not very much
- ☐ Not at all

I look forward with enjoyment to things:

- ☐ As much as I ever did
- ☐ Rather less than I used to
- ☐ Definitely less than I used to
- ☐ Hardly at all

I get sudden feelings of panic:

- ☐ Very often indeed
- ☐ Quite often
- ☐ Not very often
- ☐ Not at all

I can enjoy a good book or radio or TV programme:

- ☐ Often
- ☐ Sometimes
- ☐ Not often
- ☐ Very seldom

APPENDIX C

SOUTH OAKS GAMBLING SCREEN (SOGS)

Please indicate which of the following types of gambling you have done in your lifetime. For each type, mark one answer with an 'X': "not at all," "less than once a week, "twice a week," or "three times a week or more".

Not at all	Less than once a week	Once a week	Twice a week	Three times a week or more	
____	____	____	____	____	a. played cards for money
____	____	____	____	____	b. bet on horses, dogs or other animals (in off-track betting, at the track or with a bookie)
____	____	____	____	____	c. bet on sports (parley cards, with a bookie,, or at jai alai)
____	____	____	____	____	d. played dice games (including craps, over and under, or other dice games) for money
____	____	____	____	____	e. went to casino (legal or otherwise)
____	____	____	____	____	f. played the numbers or bet on lotteries
____	____	____	____	____	g. played bingo
____	____	____	____	____	h. played the stock and/or commodities market
____	____	____	____	____	i. played slot machines, poker machines or other gambling machines
____	____	____	____	____	j. bowled, shot pool, played golf or played some other game of skill for money

2. What is the largest amount of money you have ever gambled with any one day?

___ never have gambled ___ £10 or less

___ more than £10 up to £100 ___ more than £100 up to £1000

___ more than £1000 up to £10,000 ___ more than £10,000

3. Do (did) your parents have a gambling problem?

___ both my father and mother gamble (or gambled) too much

___ my father gambles (or gambled) too much

___ my mother gambles (or gambled) too much

___ neither gambles (or gambled) too much

4. When you gamble, how often do you go back another day to win back money you lost?

___ never

___ some of the time (less than half the time) I lost

___ most of the time I lost

___ every time I lost

5. Have you ever claimed to be winning money gambling but weren't really? In fact, you lost?

___ never (or never gamble)

___ yes, less than half the time I lost

___ yes, most of the time

6. Do you feel you have ever had a problem with gambling?

___ no

___ yes, in the past, but not now

___ yes

	Yes	No
7. Did you ever gamble more than you intended?	____	____
8. Have people criticized your gambling?	____	____
9. Have you ever felt guilty about the way you gamble or what happens when you gamble?	____	____
10. Have you ever felt like you would like to stop gambling but didn't think you could?	____	____
11. Have you ever hidden betting slips, lottery tickets, gambling money, or other signs of gambling from your spouse, children, or other important people in you life?	____	____
12. Have you ever argued with people you like over how you handle money?	____	____
13. (If you answered "yes" to question 12): Have money arguments ever centered on your gambling?	____	____
14. Have you ever borrowed from someone and not paid them back as a result of your gambling?	____	____
15. Have you ever lost time from work (or school) due to gambling?	____	____
16. If you borrowed money to gamble or to pay gambling debts, where did you borrow from? (Check "yes" or "no" for each)	____	____
a. from household money	____	____
b. from your spouse	____	____
c. from other relatives or in-laws	____	____
d. from banks, loan companies or credit unions	____	____
e. from credit cards	____	____
f. from loan sharks (Shylocks)	____	____
g. your cashed in stocks, bonds or other securities	____	____
h. you sold personal or family property	____	____
i. you borrowed on your checking account (passed bad checks)	____	____
j. you have (had) a credit line with a bookie	____	____
k. you have (had) a credit line with a casino	____	____