UNIVERSITY OF SOUTHAMPTON

The Faculty of Medicine, Health and Life Sciences

School of Psychology

Early-Informational Biases in Judgement and Decision-Making: A Dual-Process and a Dynamic-Stochastic Modelling Approach.

by

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THESIS FOR THE DEGREE OF "DOCTOR OF PHILOSOPHY"

December 2011

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

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Cognitive Psychology

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EARLY-INFORMATIONAL BIASES IN JUDGEMENT AND DECISION-MAKING: A DUAL-PROCESS AND A DYNAMIC-STOCHASTIC MODELLING APPROACH

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The thesis herein explores the relationship between early and late information in judgement and decision-making and tests a quantitative model of this relationship based on contemporary dual-process theory. The first chapter reviews literature regarding early information as a potential biasing factor in judgement and decision-making, the neglect of dual-process theory in the domain and the tendency to rely on static modelling techniques derived from economic theory. The first empirical chapter concludes that a synthesis of a static-economic decision model (prospect theory) with contemporary dual-process theory principles can better predict choice behaviour than either one approach alone. I conclude that dual-process theory provides a strong theoretical basis for understanding the cognitive processes involved in early-informational biases, but also that the quantitative approaches to modelling choice behaviour can provide valuable additional insights. The third chapter acts on this conclusion by developing a dynamic-stochastic choice model (based on a sequential sample process) which reflects four contemporary dual-process theory concepts that are relevant to early-informational biases. Simulation results of the model are presented in order to demonstrate the choice behaviour predicted by this approach. The rest of the thesis is dedicated to empirical studies designed to test the implications of these simulation results and these predicted behaviours. The empirical studies cover a range of domains including biased predecision processing during evidence gathering, stereotype bias in multi-attribute decision-making under time-pressure and the impact of expectation and accuracy motivation on visual-search decision-making. I conclude that the dynamic-stochastic modelling approach demonstrates some clear value in understanding the cognitive processes involved in these domains and the results support the use of contemporary dual-process theory as a framework for understanding judgement and decision-making. Based on this conclusion I outline some future developments for a more nuanced dynamic model including integration with a more sophisticated way of modelling type 2 processing and expansion to account for hypothetical thinking principles. I also suggest future research domains for application of the model such as expert decision-making and multi-alternative decision problems.

Contents

Declaration of Authorship

I, **Peter A.F. Fraser-Mackenzie** declare that the thesis entitled “**Early-informational biases in judgement and decision-making: a dual-process and a dynamic-stochastic modelling approach**” 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;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- 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;
- parts of this work have been published as:
    - Fraser-Mackenzie, P.A.F. & Dror, I.E. (2009). Selective information sampling: Cognitive coherence in evaluation of a novel item. *Judgement and Decision Making, 4(4)*, 307–316
    - Fraser-Mackenzie, P.A.F., & Dror, I.E. (2011). Dynamic Reasoning and Time Pressure: Transition from analytical operations to experiential responses. *Theory and Decision. 71(2),* 211-225.

Signed:

Date:

Acknowledgements

Thank you to Dr. Itiel Dror for kindling my interest in the rewarding and fascinating subject of cognitive psychology and to Dr. Sarah Stevenage for her support throughout my time at the University of Southampton.

Introduction – Thesis Overview

Topic of Interest

A well-known proverb tells us that "*first impressions are the most lasting*". Indeed, common advice is that successful first impressions are often critical to achieving positive overall impressions. The notion that early information can play a special role in judgement and decision-making (JDM) inspired the initial direction of the thesis. By necessity, therefore, much of this thesis focuses on the theories regarding the nature of the deliberation process as it unfolds over time. Tightly linked to the concept of early information is the idea that early information used during deliberation may be formed based on a degree of intuition, or 'gut feeling', regarding judgements or decisions and the idea that we may gain some sense of a solution automatically, i.e. without an awareness of explicit reasoning. This early impression can sometimes be confirmed by a more considered evaluation of the problem. However, at other times we can find that our initial impressions are wrong and a more careful consideration of the facts can overturn our first evaluation. Accordingly, the much of this thesis involves exploring the literature related to the different ways that we can reason and form judgements, and the associated cognitive psychological theories.

Much of JDM research has concerned itself with the concept of rationality and the comparison of the choices made by individuals against what might be expected based on 'normative' benchmarks. Indeed, the idea that individuals sometimes diverge from normative measures is captured by the idea that our rationality is bounded by the limits of our cognitive resources (Simon, 1957). However, the focus towards early versus late information and the comparison of intuition versus more explicit decision-processes clearly demonstrates a need to explore more than just decision outcomes. For this reason the thesis involved an exploration of the nature and characteristics of the cognitive processes involved in deliberation, i.e. the processes involved in producing the final judgement or decision.

A particularly important theory of cognition, which is strongly linked to this idea of initial impressions, is the dual-process framework (Evans, 2007a, 2007b, 2008, 2009; Stanovich, 2011; Stanovich & West, 2003; Hogarth, 2001; Kahneman & Frederick, 2002; Sloman, 1996; Rolls, 1999). Theories such as *default-interventionism* (Evans, 2007a; 2007b) that relate to the way in which reasoning processes may change over time appear to be highly relevant to the topic of interest in this thesis (Evans, 2007a). However, these approaches received comparatively little attention in the domain of JDM (Evans, 2007a), especially in the JDM domains of formal decision analysis and quantitative models of risky choice in behavioural finance.

Development of Ideas and Novel Contribution

The thesis began by contrasting and comparing dual-process explanations of reasoning processes with explanations based on a highly successful quantitative of choice - prospect theory (Tversky & Kahneman, 1992). The results of the first empirical chapter revealed a synergy between the dual-process concepts and the powerful quantitative attributes of prospect theory. The first experiment revealed that dual-process theory could be used to predict when prospect theory effects should occur. The second experiment showed dual-process theory could predict the kinds of functions produced when fitting prospect theory. Finally, and most importantly, when dual-process concepts were used to adapt prospect theory, resulting in a new "*synthesized*" model, this new model was a better predictor of choices than traditional prospect theory.

However, while this first chapter demonstrated the value of dual-process concepts in developing and improving these quantitative models of decision-making, there were some important limitations with the approach. Firstly, these formal-analysis models are static models, i.e. they do not explicitly account for the role of time or the order in which information is evaluated. This would not be a problem if order effects played no role in decision-making. However, as introduced above and in Chapter I, there are strong effects of the order of information and the issues relating to how individuals deliberate over time. Indeed, as I argue in Chapter III and VII, the reliance on static models may related to the focus towards the "Great Rationality Debate" (Stanovich, 2011), and the comparison of choice outcomes to what would be expected based on rational economic theory. As I explain in Chapter III this *deconstructive* approach of building descriptive models by adapting normative models when they fail to represent empirical choice data may not be the most effective means of advancing JDM theory in the future. Normative models ignore factors such as the order of information and the role of automatic reasoning processes in favour of mathematically provable strategies such as calculating expected values. Dual-process theory, on the other hand, considers automatic reasoning processes and how our decisions can be affected by processes beyond strategic, working-memory oriented, deliberation. It is perhaps for these reasons that these dual-process concepts have tended to be neglected in the development of quantitative models of decision-making.

For these reasons, I changed the orientation of my thesis in Chapter III with another literature review and consider a dynamic, rather than static, approach to modelling some dual-process concepts in decision-making. The rest of the Chapters aimed to test and evaluate this dynamic modelling approach.

It became clear from the outset that dual-process theory is a broad, over-arching, theory encompassing many different cognitive mechanisms and a large amount of literature from a range of disciplines. Therefore any attempt to represent the entirety of dual-process theory in a quantitative model is a task beyond a single thesis. Furthermore, some of the mechanisms of dual-process theory, e.g. parallel-competition versus serial default-interventionism (Evans, 2009), are still under debate in the literature. Instead, the aim of the thesis was to develop a dynamic-stochastic quantitative model based on just four key default-interventionist features. I then produced some simulations to demonstrate the kinds of behaviour characteristics the model predicts and these formed the basis for the empirical studies.

Due to the restriction of only four features, it must be recognized that the empirical studies cannot be seen as a test of default-interventionism or dual-process theory as a whole. There are aspects of the theories that exist outside the model’s scope and these are discussed in the final chapter. However, due to the inspiration of these theories in the model design, it was possible to discuss the model's various successes in light of the broader issues relating to current dual-process theory.

Due to this approach, the primary aim of this thesis was re-evaluated in chapter III focusing on the assessment of the sequential sample model and the implications of dual-process theory in each JDM domain. The simulations revealed four main characteristics, each of which has a related research question for empirical study:

1) The proposed sequential sample mechanism used to represent the role of type 3 processing (Evans, 2009; Stanovich, 2011), which involved the use of threshold parameters, made specific predictions regarding the volume of evidence collected and deliberation times. I assessed the extent to which empirical evidence volume/RT data support these simulation predictions?
2) The model predicted a congruency effect of early type 1 processing and subsequent type 2 processing. I assessed the evidence for this congruency effect observed in choice behaviour and response times?
3) The model was able to make continuous (as opposed to diametric, i.e. categorical) predictions. I examined whether empirical data appeaed to reflect these continuous predictions?
4) The characteristics of the sequential sample model also predicted an incongruency effect. This would not be predicted given an alternative way of modelling early-informational biases (e.g. via a race model). I examined whether the data supported this incongruency effect or not, thereby, supporting the sequential sample model rather than an alternative, race model, approach?

Thesis Outcomes

The four characteristics outlined above were supported by the empirical choice data. In addition, as each empirical chapter focused on a different type of decision, the application of a quantitative approach to dual-process concepts clearly has implications for a wide range of JDM tasks. I discuss these implications for each domain in both the empirical chapters and the final discussion chapter. I conclude by discussing the limitations of the sequential sample model used in this thesis and how these limitations can be overcome in future model development. In particular, I provide potential ideas for extension of the model that may provide a deeper representation of dual-process theory for the JDM domain.

Chapter I – Literature Review

"Logic: The art of thinking and reasoning in strict accordance with the limitations and incapacities of the human misunderstanding." – Ambrose Bierce (American Writer, 1842-1914)

Sources of Early-Informational Biases in Judgement and Decision Making

The idea that initial impressions have a special influence on judgements was demonstrated empirically through studies of order effects, whereby the same information presented to participants in a different order can have effects on judgements (Asch, 1946; Anderson, 1965; Jones & Goethals, 1972). In particular a *primacy effect* may occur in which in the information that happens to have been observed first appears to be more influential in the judgement than information examined subsequently. Tetlock (1983) provides an overview of three main explanations that have been given to this phenomenon. First is the *attention decrement* interpretation. This is the concept that due to cognitive fatigue or boredom, individuals tend to pay less attention to late information (Anderson and Hubert, 1968; Hendrick and Constantini, 1970; Stewart, 1965). The second is the *discounting* interpretation. This is the suggestion that individuals assume that later information is in some way less reliable or valid than earlier information (Anderson and Jacobson, 1965). The third suggestion is the *biased assimilation* interpretation whereby people form instant impressions based on the information, and then later information is interpreted according to this mental frame (Tetlock, 1983).

More recently, similar biases have also been demonstrated in multi-attribute decision-making. Biased predecision processing (Brounstein, 2003, for review) occurs when decision makers restructure mental representations of the decision environment in ways which favour an early favourite alternative before making a choice. More detail of these theories are discussed in Chapter IV, but the central concept is that if an early favourite alternative can be identified prior to choice, subsequent information (e.g. attributes, cues, etc.) may be processed in a distorted manner such that the judgement of the attributes of an early favourite is bolstered compared to others. The reason for distortion of the alternatives in favour of an early favourite have been attributed to cognitive dissonance (Festinger, 1957) in predecision stages, and the motivation to avoid some form of internal conflict regarding the alternatives (Janis & Mann, 1977); a need for some certainty in the choice (Mills, 1968), or a search for dominance (Montgomery, 1993, 1994; Montgomery & Willen, 1999), and the concept of cognitive coherence (Holyoak & Simon, 1999; Simon, Krawczyk, & Holyoak, 2004; Simon, Snow, & Read, 2004).

However, the primacy effect and phenomena related to biased predecision processing theories are not the only sources of early information. As far back as the 1950s, it was suggested that individuals can bring about *expectations* regarding a particular stimulus which are integrated with the exposure situation (Kelley, 1950). Thus early information can arise, not only from the task-stimuli themselves, but also from past knowledge, beliefs, expectations, etc. This is an example of how *top-down* information (e.g. past experience, beliefs, stereotypes, etc.) can play a part in our interpretation of new, *bottom*-up, information (i.e. stimulus data). This was used to explain what Nisbett and Ross (1980) termed as *belief perseverance* which describes the tendency to maintain pre-existing beliefs despite dissonant or even entirely contradictory evidence. This phenomenon has been found in areas of problem solving (Luchins, 1942), attitudes to change and stereotype perseverance (Hamilton, 1979; Allport, 1954). Studies have even revealed how individuals with polarised perspectives on issues (e.g. a group for and a group against capital punishment or nuclear weapons) can perceive the same information differently such that both their views are made stronger (Lord, Ross, & Lepper, 1979; Plous, 1991).

Similar effects even appear to occur in other domains such as visual-stimulus decision-making. Bruner and Potter (1964) presented participants with blurred pictures which were gradually brought into focus. If the stimulus began very blurry it was harder for participants to identify the image when fully focussed than if it had begun less blurry. It was suggested that people who use weak evidence to form an initial hypothesis have difficulty correctly interpreting subsequent, stronger, information (Rabin & Schrag, 1999). Even in important real-world decisions such as forensic fingerprint examination, initial impressions based on normatively irrelevant *contextual* information has been shown to affect experts' visual judgement of forensic evidence (Dror & Charlton, 2006; Dror, Charlton, & Person, 2006; Dror, Peron, Hind, and Charlton, 2005).

The discovery of these various phenomena demonstrates that early information does not simply arise from the impression of the first, normatively relevant, task-related information presented to the decision-maker. Other sources of early-informational biases can also arise from contextual information which happens to coincide with the relevant task stimuli as well as pre-existent beliefs, irrelevant pragmatic information, previous knowledge, expectations, etc., which can influence the subsequent interpretation of the task-relevant choice information. Moreover, these kinds of early-informational biases as a result of the context are not restricted to the decision-making domain. In the domain of logic and reasoning research, there are similar effects of initial impressions on the interpretation of the stimulus information. For example, Evans, Barston, and Pollard (1983) showed that individuals were less likely to agree with syllogisms that were logically valid but at first glance appear to be unbelievable, compared to those that were valid and also believable; a so-called *belief bias*. This belief bias has strong ties the ideas of early versus late information and yet the leading framework for explaining such effects in logic and reasoning research, *dual-process theory*, has tended to be neglected in the JDM literature (Evans, 2007a).

The Dual-Process Framework

Dual-process theory is not so much a single theory as a label for a broad range of more specific theories. Nevertheless, they can all be largely captured by the idea that we can process information in two ways: type 1 and type 2 processes. Type 1 processes can be broadly described as being fast, automatic, high processing capacity, and low effort (Evans, 2009). Type 2 processes can be broadly described as being slow, controlled, limited in capacity, and high effort (Evans, 2009). Type 1 processes therefore capture our more evolutionarily primitive *intuitive* reasoning abilities which are sometimes described as being formed in the autonomic set of sub-systems, or TASS, (Stanovich, 1999; 2004) also termed *system 1* (Stanovich, 1999). Type 2 processing, on the other hand, captures our more evolutionarily modern analytical thinking which tends to be more associated with language and rules. The question of defining where type 1 processing ends and type 2 processing begins is difficult, therefore Evans (2008) suggests that type 2 processing could be characterised by "*requiring a single capacity-limited central working memory*" (Evans, 2008; p.270) a requirement which is not apparent for type 1 processing.

Type 2 processes are often referred to as processes arising from *system 2* (Stanovich, 1999). However, as discussed by Evans (2009), the terms system 1 and system 2 could result in unnecessary assumptions regarding the origins and mediation of type 1 and type 2 responses. Therefore, as suggested by Evans (2008), for the rest of this thesis, where possible, I shall restrict my differentiation to type 1 and type 2 labels. Given these two ways in which we can process information, the question that arises from this dual-process theory is how these responses interact; or the "*dance of affect and reason*" (Finucane, Peters & Slovic, 2003). More specifically, the literature related to the mediation of type 1 and type 2 processing should help predict when early-informational biases would/would not be expected to occur.

Evans (2007a) states that in the situations in which both responses can input into the judgement, modelling the conflict between two responses becomes complex. Evans (2007b) outlines three ways in which this conflict may be resolved. A *pre-emptive conflict* describes an employing only one type of processing from the outset. However, in a decision-making task, in order for this mechanism to perform optimally, it must know precisely what constraining factors will be present during every decision. This presents problems when one considers that such constraints cannot always be known *a priori*, but are discovered once a task is completed; i.e. when there is no longer any uncertainty. Whilst such a monitoring system could learn to predict decision constraints, it will never perform optimally due to errors arising from uncertainty. Therefore, I believe that this weighted-mediation mechanism suffers in optimising decision-making *effectiveness*.

A *parallel-competitive* model (Evans, 2007b) describes each type of processing delivering a putative response resulting in some conflict that must be resolved. This allows both types of processing to provide a weighted input into the decision and balances the inputs according to demands. However, in many decision tasks this would be highly cognitively effortful as both types of processing would have to provide a response in every case in order for the final single preference state to be formed. Also it cannot easily account for temporal factors on deliberation as all decisions would have to wait for the slowest type of processing (type 2) to provide a response before the weighting can occur (see Evans, 2009). Accordingly, for decision-making, I see this mechanism as having a problem with *efficiency*.

A third solution may be in the form of a *default-interventionist* conflict resolution model (2007a, Evans, 2007b, 2008, 2009). Under this process, type 1 responses are theorised to provide a default response prior to type 2 processing in the overall deliberation process (Hoch & Loewenstein, 1991; Shiv & Fedorikhin, 1999; Zajonc, 1980). Type 1 processing, being rapid, involuntary and more subconscious, automatically responds to the task information before the higher-level type 2 processing. If a satisfactory decision can be made using the type 1 response, then higher level type 2 processing is not performed. In contrast, given an important decision with a great cost of error, or in which the individual is unhappy with the type 1 response, efficiency is traded off for effectiveness by allowing the more deliberate type 2 processing to intervene. As I shall explain, see this mechanism as having fewer problems that the previous two mechanisms for decision-making as well as being more representative of other JDM theories of early-informational biases.

Figure 1 shows an example of a default-interventionist model and Evan's (2006) view of how individuals may reason over time. It is proposed that individuals initially form the most plausible or relevant model which comes to mind from type 1 processing, based on the goals of the individual, their background knowledge, and the features and context of the task. This default model response is then appraised based on the *satisficing principle* for its adequacy. The satisficing principle derives from Simon's notion of bounded rationality (Simon, 1982) which refers to an assessment of the initial response on the basis of "*settling for what is good enough*" (Evans, 2007a, *p*. 18). If the model does not satisfy, then explicit type 2 processes may intervene and develop further models in an iterative fashion of hypothesis testing. Once a model is deemed satisfactory and sufficient, whether it is the first model produced by type 1 processing or a more laboriously constructed type 2 processing model, inferences and judgements can be made.

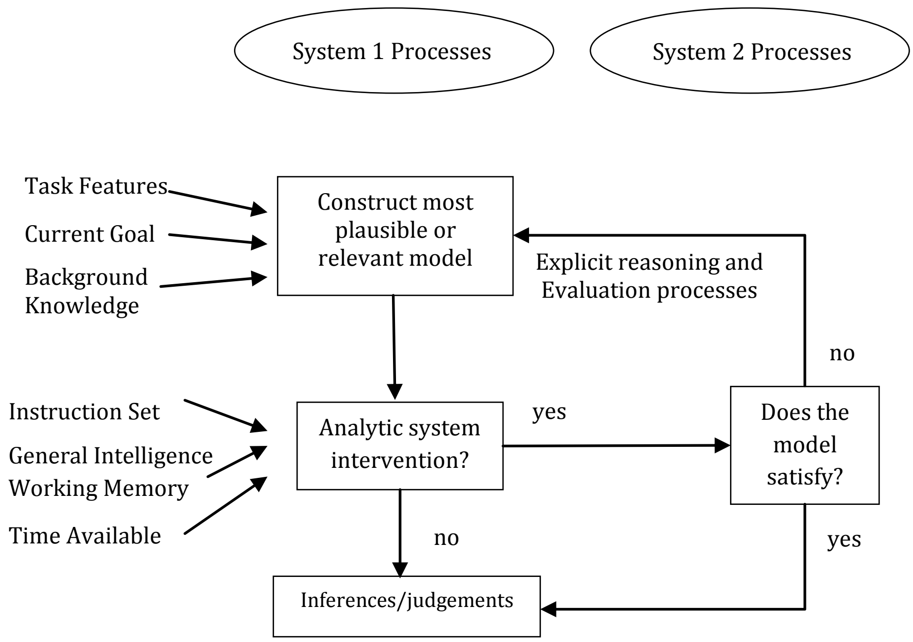

Figure 1. The heuristic–analytic theory from Evans (2006).

Note that in the heuristic-analytic theory shown in Figure 1 the assessment of whether or not the model "satisfies" is under the type 2 processes heading. However, as I shall discuss in Chapter III, both Evans (2009) and Stanovich (2011) have considered that a third type of processing (Evans, 2009), or at least a division of type 2 processing (Stanovich, 2011) may better capture this assessment process. As shown in figure 1, if analytic system intervention is not required, the inferences/judgements will rely heavily on automatic type 1 processes potentially resulting in early-informational biases. However, if analytic system intervention (type 2 processing) is employed then this late information may remove these biases.

Dual-Processes and Motivated Reasoning

What is clear from this dual-process approach is that individuals have the ability to vary their reasoning based on the satisficing principle. If the individual perceives a task to require accuracy, and assuming they possess the time and sufficient knowledge and cognitive abilities/knowledge (termed "*mindwear*" by Stanovich, 2011), then they may attempt more logical processes involving type 2 processing such as *hypothetical thinking* (Evans, 2007a). According to Stanovich's (2011) interpretation, hypothetical thinking involves a degree of "*decoupling*" (Leslie, 1987) of mental models from the current environmental stimuli in order to disengage with the intuitive solution and run mental simulations, such as envisaging different states of the world, different hypotheses, outcomes, risks, etc. Therefore, in being able to employ effective hypothetical thinking, one is better able to solve more complex tasks (Evans, 2007a). The effect of employing more hypothetical thinking is that it has the potential to reduce the role of initial impressions from the default response (i.e. the initial mental model elicited from type 1 processing) and in many cases increase the likelihood of a more accurate and rational response.

This idea can be linked to theories of *motivated reasoning* (Kunda, 1990). Although not explicitly expressed in terms of dual-process theory concepts, Kunda (1990) describes how motivation to be accurate has been shown to reduce primacy effects in impression formation, i.e. type 1 (early) processing is no more predictive of outcome than type 2 (late) processing. For example, accuracy motivation has been found to reduce the tendency to use ethnic stereotyping, and also reduce anchoring in probability judgements (Kruglanski & Freund, 1983; Freund, Kruglanski, & Shpitzajzen, 1985). It appears that accuracy motivation can result in participants using more complex and time-consuming strategies, indicating more type 2 processing (McAllister, Mitchell & Beach, 1979). In line the default-interventionism account, it seems that the initial impression is not satisficing due to the motivation to be accurate and hence more lengthy consideration occurs (i.e. employing type 2 processing).

An opposing factor to accuracy motivation appears to be time pressure. Time pressure limits the ability to perform the time-consuming mental processes (such as type 2 processing). Therefore, we should expect greater reliance on type 1 processing. Indeed, time pressure is associated with greater emotional thinking and affect heuristics (Finucane, Alhakami, Slovic & Johnson, 2000), and the consideration of moods (Noda, Takai, & Yoshida, 2007). Therefore, time pressure and accuracy motivation appear to be important in dual-process mediation, broadly acting in the opposite direction (either increasing or decreasing the role of type 1 processing).

In summary, the default-interventionist account seems to be the most flexible form of conflict resolution for the domain of JDM as it neither suffers from the effectiveness limitations of the pre-emptive conflict mechanism nor the efficiency limitations of parallel-competition. The idea that early information is more associated with type 1 processing and late information is more associated with type 2 processing also fits well with the literature regarding early-informational biases in JDM. Furthermore, the relevance to motivated reasoning literature and how certain environmental factors (e.g. accountability, accuracy motivation, time pressure, etc.) may play a role in the mediation of early-information biases suggest that the default-interventionist approach shown in Figure 1 should be particularly useful for this thesis.

Quantitative Approaches to Judgement and Decision-Making

An important part of the JDM domain is that it frequently applies quantitative approaches to modelling decision-making agents. Indeed, there are numerous choice models which are not explicitly reliant on dual-processes in their design but nevertheless seem capable of explaining the same cognitive biases. Indeed, in some cases, dual-process explanations and these quantitative model explanations often co-exist with relatively little comparative analysis. I see the domain of risky decision-making as a particularly striking example of the same research questions being tackled in two different manners with only limited comparative work between the two. As I hope to explain, the quantitative approaches to understanding risky choice behaviour tend to approach the problem from what I will call a *deconstructive* approach whereas dual-process accounts appear to follow a more *constructive* approach. I will define these terms later. First, I will explain how a leading theory of risky choice, prospect theory, was developed.

Bernoulli's (1738) *expected utility* (EU) theory proposed that individuals will choose the option with the highest expected utility where p is the probability of the utility and $u(x)$ is the subjective value assigned to the outcome:

$$EU = pu(x) \qquad \text{Eq 1.}$$

The curve of the utility function determines the risk-attitude of an individual. The most common is usually concave, i.e. $u''(x) < 0$, indicating risk aversion whereby an individual will prefer a certain \$50 payoff option to a .5 probability of \$100 or nothing option. However, individuals appear to violate some of the axioms of this normative model in their choice behaviour (Allais, 1953; Kahneman & Tversky, 1979). In particular, individuals appeared to demonstrate different risk attitudes (i.e. risk seeking or risk avoidant) depending on whether the choice involved gains and losses and whether probabilities were low or high. In order to account for this, *prospect theory* was proposed by Kahneman and Tversky (1979; and later developed further into cumulative prospect theory by Tversky & Kahneman, 1992). The theory proposes that individuals' choices may be better described by: (1) a value function $v(x)$ which differs in concavity/convexity depending on whether x is a gain/loss from a reference point, and (2) a weighting function $w(p)$ which allows for divergences from the objective probabilities p, usually some form of S-shape which over-weights low-probability events and under-weights high probability events.

$$V(x,p) = w(p)v(x) \quad \text{Eq 2.}$$

This is an example of how a normative model was adapted just enough to account for the non-normative behaviour observed by participants in experiments. However, the first observation is that prospect theory is a static-quantitative model and therefore does not differentiate between information that is examined first and information that is examined last. This is common with most quantitative approaches to JDM, whereby complex deliberation processes are summarized by static models. This would not be a problem if, as stated by the normative expected utility theory, the gathering of information played no part in individuals decision-making. However, as the literature concerning initial-informational biases demonstrates, the order in which information is processed can often have considerable impact. However, despite this important fact, theories such as prospect theory continue with a static framework to remain as close as possible to the primitives of expected utility theory. Indeed as Tversky and Kanheman (1992) state:

> "*Theories of choice are at best approximate and incomplete. One reason for this pessimistic assessment is that choice is a constructive and contingent process. When faced with a complex problem, people employ a variety of heuristic procedures in order to simplify the representation and the evaluation of prospects. These procedures include computational shortcuts and editing operations, such as eliminating common components and discarding nonessential differences (Tversky, 1969). The heuristics of choice do not readily lend themselves to formal analysis because their application depends on the formulation of the problem, the method of elicitation, and the context of choice.*" (p.317)

This appears to show that Kahneman and Tversky were concerned that their formal analysis of choice behaviour was missing some of nuances that they knew to occur in the 'black box' that contained the decision-makers' deliberation processes. Prospect theory accounts for decision outcomes, but does not explicitly model the cognitive processes involved in those outcomes. Take, for example, the phenomenon of 'loss aversion' (Tversky & Kahneman, 1981). This is the phenomenon that individuals tend to weight losses as more serious than gains of the absolute magnitude, i.e. a loss of £100 may be treated as more significant to the individual than a gain of £100. Under prospect theory, losses are described by a convex weighting function for losses compared to a concave weighting function for gains. However, the actual cognitive processes which result in this 'convexity' are not clearly defined in prospect theory. Loewenstein, Weber, Hsee, and Welch's (2001) landmark paper "Risk as Feelings" argues that this loss aversion is not '*cognitively mediated*' (Chapter

II will elaborate on this important concept) but rather has an emotional basis, taking a dual-process view that both emotional (type 1) and analytical (type 2) processes can produce assessments of risk during decision-making.

Indeed, this account has been supported by studies of brain damaged patients (Shiv, Loewenstein, Bechara, Damasio, & Damasio, 2005). Neurological evidence suggests that in order to succeed in tasks that involve weighing up risk and reward, the experience of early type 1 emotional responses are important. Patients, who have lesions to the frontal cortex in an area which allows fear to be linked to risk information, appear to make mistakes in tasks of reward reversal (Berthoz, 2006). In these tasks, a patient has to respond to one stimulus, and avoid responding to another, to gain reward. After having learnt the task, the stimuli are reversed. Although the patient is aware of the switch, they are unable to respond correctly (Berthoz, 2006), implying that fear and emotion are important to succeeding in this analytical task. It is argued that these patients are unable to link affective responses to potential future outcomes (Freeman & Watts, 1942). Indeed in direct comparison to the discussion of prospect theory, research has shown that patients with this type of damage are less sensitive to severe loss in the Iowa Gambling Task than controls who were not brain-damaged (Damasio, 1994; Bechara, Damasio, Tranel & Damasio, 1997). The results showed that the patients were quicker to take the same risk after a sudden severe loss than controls who were more averse to that high risk gamble.

Prospect theory, and many other quantitative approaches which follows formal analysis, I describe as taking a '*deconstructive*' approach to modelling JDM. What I mean by this is that they are deconstructing a normative model (e.g. expected utility theory) in order to create a behavioural model (e.g. prospect theory) which accounts for empirical data. This deconstruction usually involves adapting the normative model as little as possible (following the law of parsimony) to account for the type of divergence from the normative model observed in empirical data. Dual-process theory, on the other hand is not an adaptation from a normative model like expected utility theory. Rather, it has been developed over time from the ground up based on empirical observations and cognitive psychological theory. Therefore, I characterise it as a more '*constructive*' approach to modelling.

The result of these differing approaches is two-fold. Firstly, deconstructive quantitative models tend to be static models and therefore do not necessarily reflect temporal effects on cognition in their design. Secondly, there is frequently a void between the quantitative models in JDM and the models relating to the cognitive processes involved (see the loss aversion discussion above). I see two potential resolutions to this problem. The first is to seek for some convergence between static-quantitative models and cognitive psychological theories of decision processes. For example, one could examine whether recent advances in dual-process theory help us to better understand the causes of prospect theories value and weighting functions, or whether prospect theory can be adapted further based on the recent advances in dual-process concepts. The second solution is to develop a quantitative model of choice which is constructive rather than deconstructive, i.e. a model of decision-processes that does not begin from a formal decision-analysis standpoint, but rather begins with the basic elements of dual-process theory. Both of these resolutions would serve to bridge the gap between the quantitative models in JDM and dual-process theories of cognition.

While, dual-processes have tended to be neglected in the JDM domain (Evans, 2007a), there are some exceptions. Hammond (1996) has a cognitive continuum theory in which intuitive thinking is contrasted with analytical thinking. However, this theory does not differentiate between two types of reasoning but rather views them as two different ends of a spectrum of analysis (involving six modes) from strongly analytical, akin to a scientific experiment, to weak quasi-rational (intuitive) thought. As this theory does not differentiate between type 1 and type 2 processing temporally, it is difficult to see how it would contribute to a thesis on the role of early versus late information. Nevertheless, the notion that decision-making processes can be more than simply either heuristic or logical is representative of modern dual-process theory.

The second example of dual-processing in JDM is the contribution of Kahneman and Frederick (2002, 2005) regarding heuristics and biases associated with assessing risk and probability. Kahneman and Frederick (2002, 2005) state that, when faced with a judgement problem, '*system 1 quickly proposes intuitive answers to judgement problems as they arise*' (type 1 processes) which is followed by system 2 (type 2 processes) which '*monitors the quality of these proposals, which it may endorse, correct or override*' (Kahneman & Frederick, 2005; p.269). Essentially, this theory argues that biases are the result of employing heuristics which tend to rely on type 1 processing, but the use of type 2 processing could be used to override these effects. Take for example, the anchoring and adjustment bias first discovered by Kahneman and Tversky (1974). Anchoring and adjustment is a bias whereby beliefs, decisions, judgements, or attitudes generated through automatic (type 1) processes are altered by controlled processes (Gilbert, 1999). This has been shown to be a persistent bias and a clear example of default-interventionism at work.

Conclusion

The literature review above attempted to explain why dual-process theory is a useful framework for understanding deliberation processes in JDM. Principally, this thesis is interested in the role of early-informational biases in decision-making and default-interventionism, in particular, appears to be a promising account for this domain. However, dual-process theory, with its emphasis on explaining the moment-to-moment deliberation process is in stark contrast with the static-quantitative models such as prospect theory that have dominated the field. Indeed, it is perhaps for this reason that dual-processes have been somewhat neglected in JDM.

However, due to limitations of the quantitative models, particularly with respect their reliance on static representations, it may be that a quantitative approach simply does not lend itself to understanding the role of early versus late information in JDM. In which case, a wholly dual-process approach would seem the most appropriate manner of accounting for early-informational biases. Yet, given the strong reliance on such models in the domain as well as the additional benefits that quantitative predictions can afford a scientific investigation, I am keen to examine whether or not some degree of synthesis between a quantitative modelling approach and a dual-process approach is possible. This may help to better understand the cognitive processes behind successful quantitative models such as prospect theory.

Therefore, the initial aim of this thesis is to compare and contrast dual-process theory with a leading quantitative JDM model, prospect theory. As discussed, both dual-process theory and prospect theory are capable of explaining the role of contextual biases in decision-making. However, they both do so from very different standpoints. Dual-process theory has the strengths of explaining the cognitive processes involved in decision-making, particularly with regards to differentiating between early versus late information processing. Prospect theory, on the other hand, with its mathematical framework, can provide quantitative predictions and measures of choice behaviour. I believe a comparative study of prospect theory and dual process theory may develop our understanding and prediction of early-informational biases in decision-making by identifying if and how one can bridge the gap between quantitative models of choice and cognitive psychological models of reasoning processes.

Summary Points

- In the domain of JDM, the role of early informational biases is widely researched.
- Despite the clear relevance to this issue, much of the JDM literature has neglected to consider dual-process in the accounts.
- I suggest that this may be partially due to the tendency to rely on static-economic models which may not necessarily represent the decision processes involved.
- Therefore, the question remains as to whether dual-process theory has anything to offer static-economic models. For example, can the consideration of dual-process

theory improve our understanding of why prospect theory's functions are observed? More importantly, can the integration of dual-process theory concepts into a static-economic model improve prospect theory predictions?

Chapter II – Empirical Chapter

"*Do not indulge yourselves to judge of things by the first glimpse, or a short and superficial view of them; for this will fill the mind with errors and prejudices, and give it a wrong turn and ill habit of thinking, and make much work for retraction*." – Isaac Watts (English theologian, 1674 – 1748)

As prospect theory is a quantitative model of risky choice, the first empirical chapter will focus on numerical-based decision-making. Evans (2007a) states that pragmatic information (contextual features of the task) tends to be integrated with an individual's type 1, initial response to the task. Thus, contextual features are considered a form of early information which can act to bias choices in cases when type 1 processing is relied upon. Prospect theory, on the other hand, does not differentiate between type 1 and type 2 processing or between early versus late information. However, it is able to describe the nature and degree of bias that possible with respect to weighting and value assigned to alternatives. The following empirical chapter examines prospect theory and dual-process explanations of the role of this early contextual information in numerical decision-making. The studies demonstrate that predictions based on prospect theory combined with dual-process concepts are often better than predictions based on prospect theory alone. This suggests that, despite its neglect, dual-process not only have the ability to improve our understanding of theories such as prospect theory, but may also be important in its own right for the development of new quantitative models of decision-making.

Bounded Quantitative Judgement of Numerical Information: Providing Explanations for Distortions in the Evaluation of Forensic Evidence, Alternative Gambles, and Investment Performance via a Synthesis of Prospect Theory and Dual-Process Theory

Abstract

This chapter aims to improve understanding of the effect of contextual task-features on the interpretation and judgement of numerical information. To this end, I considered a synthesis of prospect theory and dual-process theory concepts in order to better understand the nature and characteristics of bounded quantitative judgements. I demonstrate the value of this synthesized approach in interpreting the findings of three studies in different domains all involving judgements of numerical information. The first study explored the effects of framing and risk-information modes on forensic evidence in court. Prospect theory was beneficial in predicting the effect of risk-information modes on the perceived strength of evidence against the suspect. However, dual-process theory was required to predict when these risk-information mode effects would/would not occur. The second study explored the effects of risk-information modes in gambling on horse-racing. Again, dual-process explanations complemented prospect theory, this time predicting the kinds of probability weighting functions we should expect to be found under each mode. The third study, which examined the judgement of investment performance, directly compared a normative model, traditional prospect theory, and a model based on a synthesis of dual-process concepts and prospect theory. The results showed that the synthesized model better predicted participants' judgements of investment performance. In doing so, I also demonstrate evidence of a new type of bounded quantitative heuristic – the '*place-value heuristic*'.

Introduction

A leading framework for quantifying bias effects in risky financial decisions is *prospect theory* (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). The ability of prospect theory to capture choice behaviour in mathematical functions based on quantitative-economic models is a considerable strength. However, a major criticism is that "[*v*]*irtually all current theories of choice under risk or uncertainty are cognitive and consequentialist. They assume that people assess the desirability and likelihood of possible outcomes of choice alternatives and integrate this information through some type of expectation-based calculus to arrive at decisions.*" (Loewenstein, Weber, and Hsee, 2001). An alternative approach stems from the various ideas that emerge from *dual-process* theories (Evans, 2006;

Evans, 2009; Stanovich, 2004; 1999; 2011; Stanovich & West, 2003; Hogarth, 2001; Kahneman & Frederick, 2002; Sloman, 1996, Rolls, 1999). These theories allow judgements to be driven by one of two "minds": a more evolutionarily primitive, rapid, automatic assessment; or a more evolutionarily modern, slow, and analytical assessment. However, as discussed in Chapter I, dual-processes have generally been neglected in much JDM research (Evans, 2007a). A major reason for this may be that it is difficult to determine exactly how to bridge the gap between quantitative "*cognitive and consequentialist*" (Loewenstein, Weber, and Hsee, 2001) models of decision-making (e.g. prospect theory) and descriptive cognitive psychological models of reasoning processes (e.g. dual-process theory).

This study focuses on the role of contextual biases and how they act on the judgement of numerical information. The three task features considered in this chapter are *frames, information modes,* and the *numerical values* themselves. To establish connections between the two theories, I consider research examining levels of numerical processing and use this to bridge the gap between dual-process theory and prospect theory. Then, in three experiments, I demonstrate that the effects of contextual biases are better predicted by a synthesis of prospect theory and dual-process theory than by predictions made by prospect theory alone. I demonstrate that this synthesized approach has the potential to help to understand the cognitive processes involved in the formation of prospect theory's weighting and value functions, thereby extending the predictive scope of prospect theory into new domains. In addition, I show a synthesis of dual-process concepts and prospect theory can out-perform traditional prospect theory and a normative model. I conclude by discussing the implications of the experimental results for the quantitative model of decision-making and future directions.

Framing Effects

The framing of a decision refers to how it is presented; specifically, which information is made explicit and which implicit. Evidence suggests that the preference between two alternatives can be reversed by the effect of *framing*. Levin, Scheider and Gaeth (1998) describe three ways in which framing experiments are usually performed: Risky Choice Framing, Attribute Framing, and Goal Framing. *Risky Choice Framing* experiments usually involve one certain, or riskless prospect, and another all-or nothing risky prospect. The classic example of this was Tversky and Kahneman's (1981) 'Asian Disease Problem'. Their findings indicated that presenting a positive frame (e.g., explicit information suggests the potential to *save* lives) is less likely to result in risk-taking than negative framing (i.e. suggesting the potential to *avoid losing lives*). *Attribute Framing* experiments explore the effects of descriptive valence on the information processing of a prospect. Levin and Gaeth's (1988) study provides an example of this: participants were asked to sample identical minced beef that was either positively framed (75% lean) or negatively framed (25% fat). It was found that the positive (cf. negative) frame resulted in participants rating the beef as better (in terms of taste and of being less greasy). *Goal Framing* experiments focus on the potential benefits (cf. loss) of approaching a goal (cf. avoiding certain behaviour). In these experiments, comparisons are made between the prevalence rates of the behaviour in question under the different frames. Overall, results of these experiments suggest that people are more likely to engage in the desired behaviour if the focus of the framing is avoiding loss rather than approaching gain (e.g. Tversky & Kahneman, 1991; Thaler, 1980).

In summary, framing may be summarized as the 'glass-half-full/-half-empty' property of information, whereby both representations of the same problem are normatively equivalent if we consider all implications of the information. However, being informed that a glass is 'half full' initially feels more positive based on our first impression of the stated information.

Prospect Theory's Value Function Explanation of Framing Effects

According to prospect theory, value is perceived relative to a reference point (rather than perceived in an absolute fashion), and framing is said to influence the position of this reference point. For example, a 'glass-half-full/half-empty' is considered a positive/negative frame because it implies an increase/decrease from 'an empty/a full glass' reference point. This relative valuation is important, particularly since individuals tend to perceive losses as more serious than gains; an effect termed *loss aversion*. Prospect theory attempts to capture this notion of loss aversion through the use of different *value functions*, which depend on whether the situation is perceived as a gain or a loss. For example, the perceived value $v(x)$, of a payoff, x, predicted by prospect theory, is shown in eq 1, where α, $\beta > 0$ measure the curvature of the value function for gains and losses respectively, and the λ is a coefficient for loss aversion, which acts to amplify the subjective absolute value of a loss compared to the subjective absolute value of a gain (Tversky & Kahneman, 1992):

$$v(x) = \begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda(-x)^{\beta} & x \leq 0 \end{cases} \qquad [1]$$

Risk-Information Modes

While framing is often used to describe any form of bias driven by the way a problem is described, I differentiate framing, as defined above, from that of the information *mode*. I define the information mode as the unit or scale representation of the information. In this chapter, the focus is on the modes used to represent risk information. Gigerenzer and Hoffrage (1995, 1999) demonstrated that people perceive expected frequency data (e.g. a 1 in 4 chance) differently to objectively equivalent percentage data (e.g. a 25% change). Indeed, it has been argued that the use of frequencies may improve assessments of probability as they are more intuitive (Gigerenzer & Hoffrage, 1995). For example, Slovic, Monahan, & Macgregor (2000) demonstrated that estimates of risk are often higher when presented as relative frequencies (cf. in probability format). Rottenstreich and Kivetz (2006) argue that risk-information modes which elicit/do not elicit a probabilistic mindset tend to result in people relying on/neglecting judgements of likelihood. Indeed, it has been argued that individuals are generally more competent at reasoning based on a frequency mode than a probability mode (Cosimides & Tooby, 1996).

However, Evans, Handley, Perhnham, Over and Thompson (2000, see also, Evans & Over, 1996) argued that, while frequency formats may be more intuitive to our more implicit, primitive, mental processes, one must also consider higher-level, explicit, mental processes and our ability to construct and manipulate mental models (Evans, et al, 2000). Therefore, the extent to which risk-information modes impact on performance may be more nuanced than the basic argument that frequency modes, per se, improve decision-making. For example, as I shall expand on later, modes which are/are not conducive to type 1 processing are not necessarily beneficial/inhibitory in tasks which are type 2 processing oriented, such as complex reasoning about numerical information (Evans, et al, 2000).

Prospect Theory's Probability Weighting Function

As the perception of numerical risk-information can potentially be influenced by risk-information modes, I consider how prospect theory may capture these distortions. Prospect theory incorporates the notion that individuals may not weight alternatives by their objective probabilities. This is captured by prospect theory's *weighting function*, *w*, usually via an inverse S-shaped function, resulting in low/high probabilities being over/under weighted for values of $\gamma < 1$. For example, Tversky and Kahneman (1992) employed the following weighting function:

$$w(p) = p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma} \qquad [2]$$

According to prospect theory, the value an individual attaches to a prospect, *V*, is not the expected utility (EU), i.e. is not simply a probability weight, *p*, applied to an individual's utility function $u(x)$ on a payoff, *x*:

$$EU = pu(x), \qquad [3]$$

rather, it is a function combining the weighting function, w, and the value function, v;

$$V(x, p) = w(p)v(x). \quad [4]$$

Prospect theory is able to capture the degree of divergence between the weight individuals attach to likelihoods and the actual probabilities. Indeed, much work has stemmed from the comparison of eqs. 3 and 4, in an attempt to determine which model best accounts for behavioural outcomes. In order to understand how our cognitive processes might produce these functions, we must turn to cognitive psychological theories of judgement and reasoning.

Dual-Process Theory and Levels of Numerical Processing

As discussed in Chapter I, many theories are inspired by the concept of dual-processes but they all have a common argument: individuals can process information in two generally distinct manners. Type 1 processes are generally fast, automatic, high in processing capacity, and low in effort. These processes appear to be more instinctive in nature; a style of reasoning we share with animals (Evans, 2009). Type 2 processes are generally slow, controlled, limited by working memory, and high in effort. However, these processes afford us the ability to perform abstract reasoning and hypothetical thinking (Evans, 2007a). These two types of reasoning are not necessarily separable into two distinct cognitive systems (Evans, 2009). However, they are often referred to as *system 1* and *system 2* processing respectively (Stanovich, 2011, Frederick, 2005).

As discussed in Chapter I, Kahneman and Frederick (2002, 2005) state that, when faced with a judgement problem, '*system 1 quickly proposes intuitive answers to judgement problems as they arise*' (type 1 processes) which is followed by system 2 (type 2 processes) which '*monitors the quality of these proposals, which it may endorse, correct or override*' (Kahneman & Frederick, 2005; p.269). This description has strong echoes of Evan's (2007a; 2007b; 2009) default-interventionism theory.

Prospect theory and dual process theory originated in different disciplines, the former being behavioural economics/finance orientated and the latter developed from learning, logic and reasoning research. Consequently, in order to form connections between these theories I examine how dual process theory might capture the processing of numerical information. In particular, I explore how type 1 processing could propose an intuitive response to numerical values without fully engaging type 2 processing.

Levels of Numerical Processing

Several studies have shown that we possess two distinct and dissociated quantitative processing systems (Lemer, Dehance, Spelke, & Cohen, 2003; Pica, Lemer, Izard, &

Dehaene, 2004; Gordon, 2004). The lower level system is a primitive approximating system, which enables individuals to differentiate between quantities and to order according to magnitude. Animals also appear to employ this system. For example, behavioural studies have revealed that monkeys can learn to order sets based upon their magnitude (Brannon & Terrance, 1998), and this has even been demonstrated in untrained animals (Hauser, Carey, & Hauser, 2000). Infants, even those less than one year of age (i.e. before the acquisition of words for numbers), have also been shown to exhibit similar approximate number discrimination and comparison abilities (Brannon, 2002; Wynn Bloom, & Chiang, 2002). In addition, certain Native American tribes who do not possess consistent words for numbers above 4 and 5, have also been shown to succeed in non-verbal numeracy tasks (Pica et al., 2004; Gordon, 2004). By contrast, and apparently unique to humans, a higher level of numeracy enables us to represent, learn, and manipulate specific numbers using symbols; allowing the complex calculations and hypothetical transformations required for higher level mathematics (Lemer et al., 2003). Studies of brain damaged patients reveal that this higher level numeracy appears to be distinct from other lexical-semantic components of knowledge, to the extent that it may be processed in a dissociated system. A study of a patient with semantic dementia (Cappelletti, Butterworth, & Kopelman, 2001) showed that the disease significantly reduced the patient’s conceptual knowledge and, thus, their ability to perform tasks such as being able to name, classify, match, and judge the size of objects in pictures. Despite this severe degradation in semantic knowledge, the patient could still perform well at reading, writing, and even transcoding Arabic and written verbal numerals, and was able to compare magnitudes when they were presented as numbers. However, the patient performed poorly when asked to discuss the semantics associated with numerical ideas such as arithmetical operations or when asked questions concerning personal number facts (Cappelletti et al., 2001).

There appears to be a striking link between the two levels of quantitative processing and the two reasoning systems associated with dual-process theory. For example, using type 1 processing we can rapidly and automatically order 645 and 215 in terms of magnitude without any need to calculate the exact difference. Similarly, just by a brief glance at Figure 1 it is clear that the number of points in the left figure is larger than that of the right figure. However, should the need arise, we are also capable of employing type 2 processes in order to calculate the exact difference (430) or to discover the fact that the number of points in the left box is exactly three times as many as in the right. This dual-process approach to numerical processing, a rapid and automatic, heuristic, assessment (type 1) versus slow but more precise, calculative, assessment (type 2) may help to explain the distortion of numerical values and help identify how dual-processes can be linked to prospect theory.

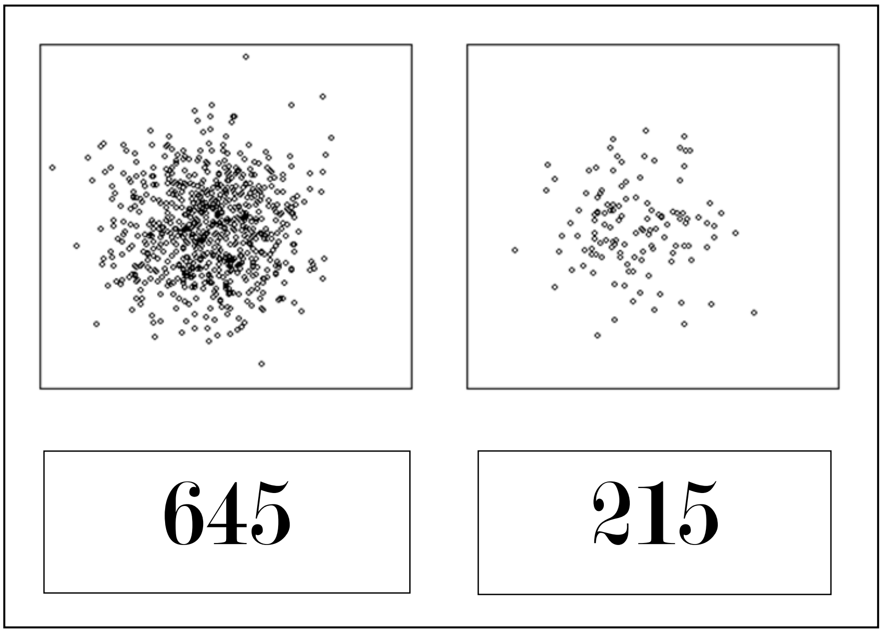

Figure 1. *The number of dots and the symbolic representation in numerals can be rapidly and automatically ordered by magnitude using type 1 processes but also type 2 processing allows complex calculations on the numbers to be made.*

A Dual-Process Model of Bounded Quantitative Judgement

The model represented in Figure 2 shows the heuristic-analytical (dual process) theory of logical reasoning (Evans, 2006) with two additions (in italics) based on additional literature; the lower-level and higher-level quantitative processes. Based on this default-interventionist approach (Figure 2) the process of bounded quantitative judgement might occur as follows: (1) contextual information gathered by type 1 processing may combine with, direct, and possibly distort, the initial, *default*, heuristic assessments of numerical magnitude produced by a lower-level quantitative system. This forms the initial mental model of the choice problem (2). The accuracy of this initial, type 1, model relies heavily upon whether the information is presented in a manner which is intuitive to type 1 processing. If the information is not presented intuitively (i.e. in a format conducive to type 1 processing), biases may occur. This initial model is then assessed (3) against a satisficing principle (Evans, 2007a) or “feeling of rightness” (Thompson, 2009), which determines whether this low level heuristic assessment is perceived to be good enough[1]. If "yes" (4) a judgement can be made based on this low level magnitude heuristic, if "no" (5) higher level quantitative calculations may have to be employed to improve the mental model's precision.

Therefore, if the default type 1 model is relied on for a decision (i.e. a (1), (2), (4), or a (1), (2), (3), (4) process in Figure 2) then numerical processing accuracy depends on the extent to which the risk information mode or frame is conducive to type 1 processing and has produced a rapid but accurate mental model. If, however, the default model is assessed to be not satisficing (3) and type 2 interventions are to be elicited, then the effect of the risk-information modes or frames may have a reduced effect or be entirely removed at (5). This is likely to depend on the individual's mathematical abilities.

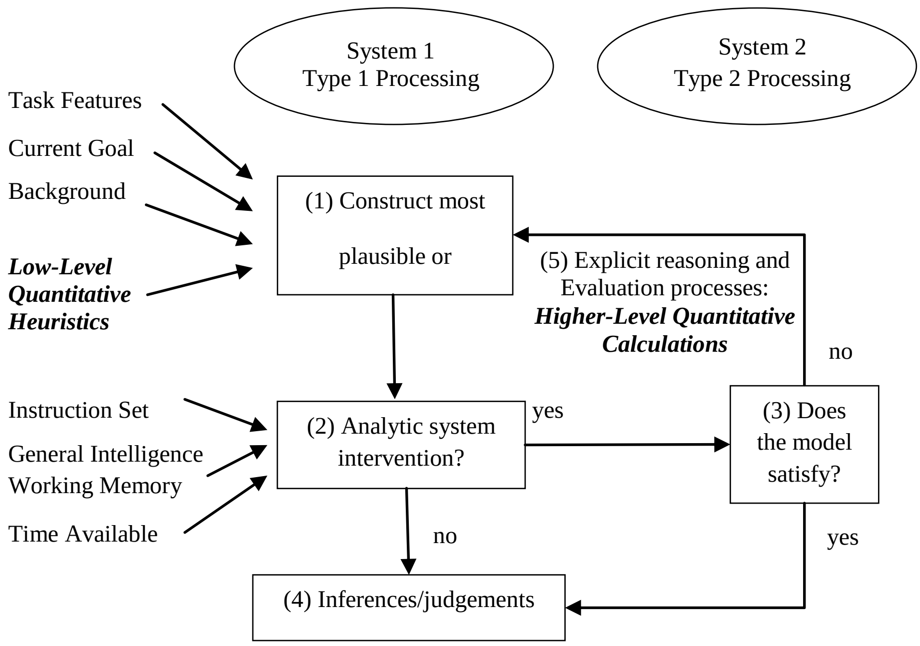

Figure 2. The heuristic–analytic theory (from Evans, 2006) with the addition of levels of quantitative processing (in italics): a dual-process account of bounded quantitative judgement.

1 While his assessment is shown as a system 2 process, Stanovich (2011) recently proposed that this type of assessment should be separated from other system 2 processes (algorithmic versus reflective minds), and Evans, (2009) considered the potential for a third type of processing (type 3). See Chapter III for more discussion of these proposals.

Linking the Dual-Process Explanation of Bounded Quantitative Judgement with Prospect Theory

As discussed earlier, some risk modes (e.g. relative frequencies) may be more conducive to type 1 processing than others (Gigerenzer & Hoffrage, 1995; Cosmides & Tooby, 1996; Rottenstreich & Kivetz, 2006). These risk modes may lend themselves to more effective low-level quantitative heuristic estimates (type 1 processing) of magnitude, i.e. assuming higher-level quantitative calculations (type 2 processing) are not involved. Those risk modes which are least conducive to type 1 processing should result in the greatest bias (assuming type 2 intervention does not occur). The degree of this bias ought to be captured by prospect theory's weighting function, which can be estimated on the basis of a set of decisions. However, based on a default-interventionist view, such effects should be removed if type 2 processing is involved (Evans, 2008; Kahneman & Frederick, 2002, 2005).

The dual process approach discussed above can also account for loss aversion. As discussed in Chapter I, it has been proposed that loss aversion has an emotional (type 1 processing) basis (Loewenstein, Weber, Hsee, & Welch, 2001), and this has been supported by studies of brain damaged patients (Shiv, Loewenstein, Bechara, Damasio, & Damasio, 2005). Accordingly, I hypothesize that type 1 (low-level) magnitude judgements of a number may more greatly exaggerated in loss situations than in gain conditions and that it is this effect which is captured by prospect theory's coefficient for loss aversion, λ, in the value function (eq. 1). Importantly, it is not only real losses that may result in loss aversion, but also *illusory losses*, i.e. losses which, based on low-level (type 1) magnitude heuristics, appear to be greater than they are in reality.

In order to test the hypothesized relationships discussed above, I consider, in three experiments, the impact of information frames and risk-information modes on numerical judgement. The first study is in the domain of forensic court evidence - a clear departure from the usual domain of prospect theory. Nevertheless, I do see potential for prospect theory to apply. The second study examines horserace betting, a domain which readily lends itself to the application of prospect theory. The third study explores investment performance, a domain strongly associated with prospect theory. Despite differences between the experiments in terms of their proximity to domains normally associated with prospect theory, I demonstrate that prospect theory has some value in predicting the effects of the contextual biases in all three cases. However, I also show that in all three domains a synthesis of prospect theory and the dual-process approach provides the most effective account of the effects of contextual biases in quantitative judgement. Indeed even in the third study, the domain of which is most closely aligned to prospect theory, I demonstrate that the synthesized approach is better than a traditional prospect theory, or normative approach.

Experiment 1

Information Frames and Modes in Forensic Court Evidence

The experiment focused on the presentation of probabilistic forensic evidence (e.g. the evidence suggests that there is a 90% chance that the defendant's fingerprints match those found at the crime scene) and test the extent to which contextual biases influence innocent/guilty judgements based on this evidence. Given that forensic evidence could be presented in terms of a probability or frequency mode, as well as being framed in terms of the likelihood of the fingerprints matching or not matching those of the defendant, there is a 2 x 2 set of ways to describe forensic evidence (see Table 1). The aim is to use dual-processes and prospect theory to predict the effect of these alternative representations of information on innocent/guilty decisions.

Table 1. A demonstration of how two modes of representation and two frames can result in four ways of representing objectively equivalent forensic evidence.

	Type 1 Eliciting "*Match*" Frame	Type 2 Eliciting "*Non-Match*" Frame
Type 1 conducive *Frequency* Mode	9 in 10 chance that the two fingerprint marks originate from the same source	1 in 10 chance that the two fingerprint marks do *not* originate from the same source
Type 1 non-conducive *Percentage* Mode	90% chance that the two fingerprint marks originate from the same source	10% chance that the two fingerprint marks do *not* originate from the same source

Studies in reasoning have demonstrated that negative propositions (i.e. propositions involving 'not', or 'non-') are more difficult to process and individuals take longer to comprehend the information (Schroyens, Shaeken, Fias, and d'Yewalle, 2000). Accordingly, numerical values under a *not*-match frame (e.g. probability, *p*, of *not x*) may be more computationally demanding. Therefore there is a greater requirement for type 2 processing and higher level quantitative processing in order to convert the information into the likelihood of fingerprints matching. For example, given the probability of *not-x*, one must perform explicit mental processes to calculate the probability of x (i.e. probability of $x = 1-p$)[2]. Whereas, a frame which directly corresponds to the likelihood of guilt (i.e. the match frame), is already in the appropriate form (i.e. the probability of $x = p$). Consequently, I expect that the latter information may be more readily assessed by type 1, low-level, processing without type 2 interventions being required. If this is true, I hypothesize that type 1 processing is more likely to be relied upon in the "match" frame but type 2 intervention may be elicited in the "non-match" frame. Type 2 processing intervention should be better able to remove any negative contextual effects associated with numerical information. Consequently, I predict an attenuation of any distortive effect of risk-information modes in the non-match compared to the match frame on the evaluation of the evidence. In order to predict what these contextual distortion effects might be, I turn to prospect theory.

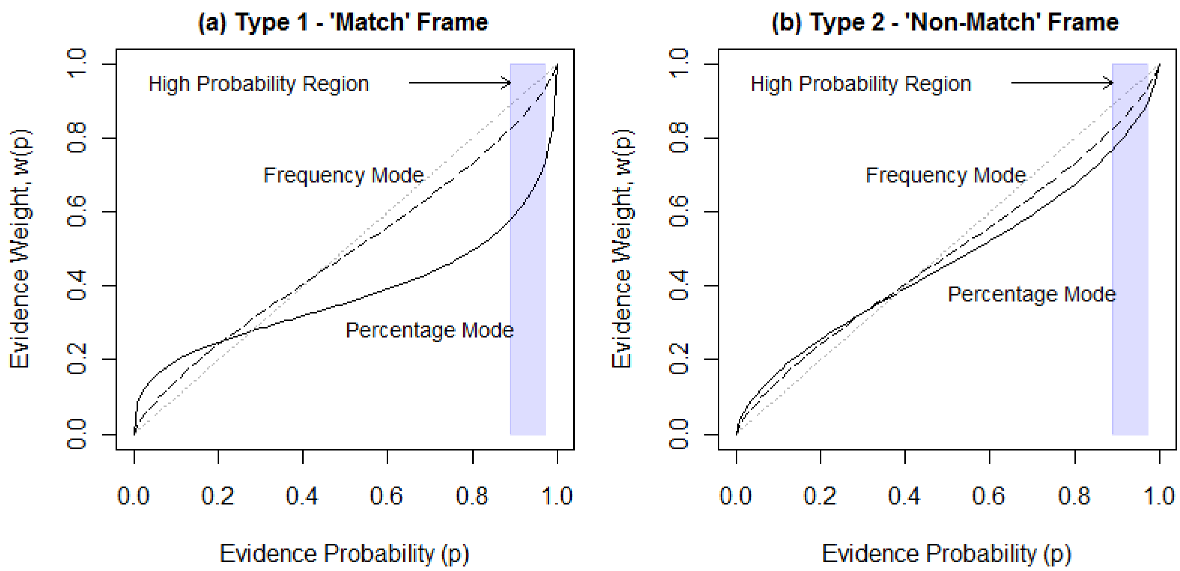

Figure 3. An example of the expected effect of a typical S-shaped bias in prospect theory's probability weighting function on the perceived strength, w(p), of forensic evidence (near 1 indicates a strong "guilty" weight, whereas near 0 indicates a strong "innocent" weight). A high probability region, within which forensic evidence would lie, is highlighted. The strongest bias would be expected when type 1 processing is relied on (match frame) and the mode is not conducive to type 1 processing (percentage mode).

Prospect theory captures the impact of probabilities on assessment via the weighting function, w. The traditional prospect theory function involves the underweighting of high

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[2] Extrapolating from this effect, this theory would predict that numerical values associated with a double negation (e.g. probability of *not, not x* is p) would require even more type 2 processing to determine the probability of p (i.e. probability of $x = 1-(1-p)$, therefore probability of $x = p$).

probabilities and overweighting of low probabilities (S-shaped function); determined by the γ parameter. If it is the case that the perception of probabilistic information is more inaccurate when interpreting percentage (cf. frequency) modes, as found by Gigerenzer & Hoffrage (1995), we should expect the percentage mode to result in a more pronounced S-shape weighting function of objective probabilities.

The more pronounced S-shaped weighting function under percentage (cf. frequency) mode would result in high probabilities being more underweighted. In fact, forensic evidence, and hence the probabilities used in the following experiment, are only presented in court if they are of sufficiently high probability (evidence which is of low validity is of little value to a court). Therefore, I would expect lower perceived strength of forensic evidence under percentage mode than under frequency mode (see Figure 3a). If this is the case, the synthesis of dual-process theory and prospect theory would predict fewer guilty judgements under percentage (cf. frequency) mode as the evidence is afforded less weight in the match frame (see Figure 3a).

Critically, as discussed earlier, dual-process theory predicts when the information mode should have less effect on the weighting function. Evans, Handley, Perhnham, Over and Thompson (2000) argue that if the task involves type 2 processing (e.g. explicit reasoning about a numerical word problems) then such framing modes ought to have a reduced effect; resulting from type 2 processing intervening and remove the effects. Therefore, I predict that the intervention from type 2 processing, triggered to deal with the negation "not", would reduce the contextual effect of the risk-information mode (frequencies versus percentages) on the perceived strength of evidence (see Figure 3b). Therefore, as shown in the comparisons of Figures 3a and 3b, I predict an interaction, in which there is a greater effect of risk information mode under the type 1 eliciting "match" frame than in the type 2 eliciting "non-match" frame. These predictions are tested in the following experiment.

Method

A fingerprint from the scene of a crime was presented as a source of forensic evidence in a hypothetical court case. Participants were told the likelihood of the evidence matching that of the defendant and were asked to make judgements of the defendant's guilt. The only objective manipulation involved the likelihood of the forensic evidence being correct. This was manipulated between subjects, along with the risk-information mode (percentage or likelihood format) and the framing of the information (whether the numerical values represent the chance of the fingerprint matching or not matching; i.e. $p_{(\text{match})}$ or 1-$p_{(\text{match})}$). As the weighting function in prospect theory predicts an effect of the information modes on the perceived strength of evidence, this should impact on the proportion of guilty/innocent verdicts.

Participants

In total, 123 undergraduate participants were recruited, including 80 females and 43 males between the ages of 16 and 47 (M =18.9, SD = 6.6). They were given course credits for their participation.

Design and Procedure

Participants were undergraduate students at the University of Southampton rewarded with course credits. They were given an information and consent form prior to each task (see appendix A for an example) and were fully debriefed after the experiment. The experiment was carried out in an experimental laboratory. A description of a shoplifting case was constructed, with fingerprints being the only available evidence. The participants were presented with an instruction sheet detailing what was required of them. Any questions they had were then answered. Once the participants were clear on the instructions, they were presented with a sheet of paper detailing the crime, alongside the evidence against and in defence of the accused. The participants were then given as long as they needed to read the case and to draw a verdict of ‘guilty’ or ‘not guilty’. Case description for experiment 1:

> ‘*A person was accused of shoplifting. According to a shop owner, when he closed up for the evening he found that a camera was missing from its display and it had not been paid for. During a police raid of a warehouse of stolen goods, the camera was recovered, identified by its serial number. Police recovered several partial finger marks that were deposited on the camera. One of the partial finger marks was searched for on a computer database and the accused was identified as a possible match, and then further analysis was carried out by a fingerprint expert. The accused stated that he had not been shopping in the store on the day the camera was stolen, and that he had spent the day with a friend. His friend testified that this was true, but there was no further evidence to confirm this. A fingerprint expert testified that there was little clarity and quantity of comparable data within the crime scene mark, but went on to say that following his analysis, he estimated that in (… x% / x out of 100…) cases similar to this case the accused (…would / would not…) have deposited the finger mark on the camera.*’

Design

The experiment used a between-subjects design. There were three independent variables: the information indicating the likelihood that the fingerprint matched that of the defendant, the mode of representation, and the framing. Three levels of the likelihood i.e., quantitative information, were employed ($p_{(match)}$ = .93, .91, or .89). Both percentage (e.g., 93% chance of it being a match) and frequency forms of representation were employed (e.g., in 93 out of 100 cases it was a match). The framing was either "match" (e.g., 93% chance of the fingerprint matching that of the defendant) or "not match" (e.g., 7% chance of the fingerprint not matching that of the defendant). The dependent variable was the participants' guilty/innocent verdict. These different conditions were presented between participants such that there were twelve between-subjects experimental groups.

Results and Discussion

Probabilistic Evidence Data

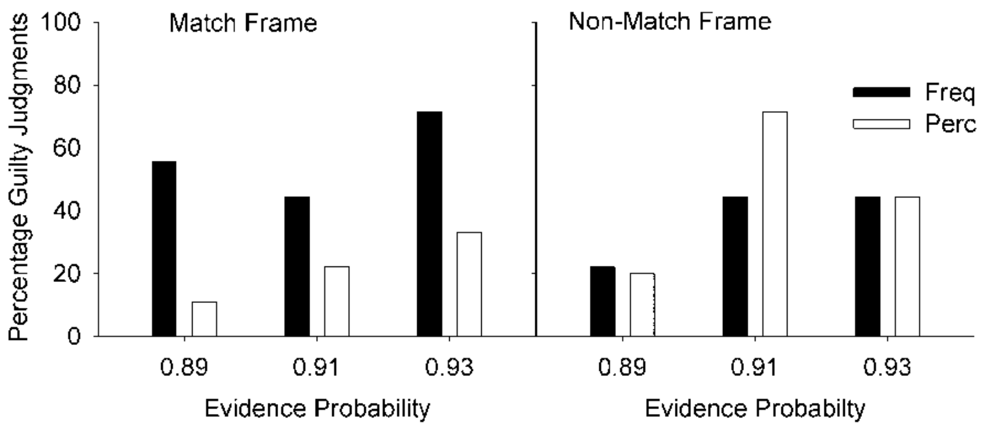

Figure 4. The percentage of individuals that judged the accused guilty under each frame, mode, and evidence probability condition

The results of the experiment are summarized in Figure 4. In order to test the null hypothesis that the frames and modes of presentation do not, but the accuracy of the evidence does, influence judgements of guilt, logistic regression analysis was conducted, with a guilty/not guilty judgement as the dependent variable. The results revealed that objective probabilities were significantly predictive of choices at the 5% level (one-tailed), $b = -24.32$, SE = 12.97, $p < .05$. In addition, as predicted by the synthesis of dual-process and prospect theory, the percentage format resulted in significantly fewer guilty judgements than the frequency format, $b = 1.59$, SE = 0.63, $p < .05$. While the framing alone did not appear to influence guilty judgements, $b = 0.84$, SE = 0.58, $p > .05$. In addition, as predicted by the synthesis of dual-process and prospect theory, an interaction between framing and mode was a significant predictor of guilty judgements, $b = -1.83$, SE = 0.85, $p < .05$. Indeed, post hoc tests revealed that while there was a significant difference between frequencies and percentages in the rates of guilty verdicts under the match frame ($p = .012$), there was no significant difference in the non-match frame ($p = .700$).

The results are consistent with the hypotheses that formats of presenting information which elicit greater need for type 2 processing (i.e. the non-match frame) should reduce the overall effect of contextual biases on the weighting of evidence (i.e. the effect of frequency versus probability modes on the weighting of evidence). However, if a format does not tend to elicit a requirement for type 2 processing (i.e. the match frame), we should observe a greater effect of contextual biases on the weighting of evidence as type 1 processing is relied upon. This interaction is shown in Table 2. The results confirm the dual process theory prediction that there should be a greater difference in guilty verdicts between the risk information modes under the match frame (i.e. greater effect of contextual biases). Furthermore, as predicted by the probability weighting function in prospect theory, the forensic evidence under the percentage mode appears to result in fewer guilty verdicts, indicating that participants were less convinced by the strength of the evidence. Again, as predicted by the dual-process approach, this effect of the contextual information is attenuated in the 'non-match' frame, presumably due to increased reliance on type 2 processing intervention.

Table 2. The percentage of participants that chose the "guilty" verdict under the match and non-match frames for both frequency and percentage information modes.

	Percentage Guilty Verdicts	
	Match Frame	Non-Match Frame
Frequency Mode	56%	37%
Percentage Mode	22%	42%

While this study does suggest that the information modes used can influence the weighting of probabilities in line with prospect theory, this conclusion is only inferred from the comparison of the interaction in Table 2 and the predictions in Figure 3. It would be interesting to employ prospect theory more directly over a greater range of probability values. In doing so it would be possible to fit prospect theory functions to behavioural data and determine the extent to which the dual-process predictions regarding the effects of the information mode are correct. Specifically, I aim to determine whether fitted prospect theory parameters reflect the prediction that frequency modes should tend to be less biased than probability modes.

Experiment 2

The Effect of Pricing Modes in Racetrack Betting

Experiment 2 involved a manipulation of the information mode in the betting domain, and as such, provides an interesting development to the investigation of information modes in forensic court evidence. In particular, while horse odds are always applied in a single frame (i.e. the likelihood of the horse *winning*), the probabilities involved are of a much greater range than those associated with forensic evidence – especially that presented in criminal cases (which is associated with very high probabilities, in a narrow range) . By contrast, the winning probabilities of horses (calculated from their odds) tend to range from high (the favourite), to very low (longshots). Accordingly, while the forensic evidence domain can provide insights into the effects of risk-information modes on weighting functions in near certain situations (see Figure 2), the betting domain offers the prospect of developing insights into their effect over a range of likelihoods which allows for the fitting of model parameters.

Normative Models and Violations of Stochastic Dominance

In order to evaluate whether risky choice behaviour is consistent with normative models, the concept of stochastic dominance is important. First-order stochastic dominance is said to hold if a gamble can be ordered as superior to another gamble based on expected return (the mean outcome). Second-order stochastic dominance is said to occur if a gamble can be ordered with respect to the variance of outcomes (i.e. risk). Normatively, the risk-information mode should not affect objective measures of expected value or risk. Thus, for the same individual (i.e. with the same utility function), stochastic dominance should hold for both fractional odds and decimal returns. That is, three prospects which are ordered, $a \geq b \geq c$, under the fractional odds pricing mode, should be ordered identically, by the same individual, under a decimal returns format. If the same individual orders the same prospects differently between these formats, then a violation of first or second order stochastic dominance has occurred. Of course, one might expect random violations in this ordering simply through random miscalculations. Indeed, such response variability is common in studies of risky choice, with a median rate of preference reversal of 23% (Scott, 2006). However, if the violations are systematically related to contextual factors then this would suggest that these factors distort the individuals' perception of the risk information.

Risk-Information Modes in Betting

Fractional odds format is in an expected frequency format whereby *X*/1 implies that the horse should lose *X* and win one race out of a hypothetical *X*+1 identical races (i.e. "*20 to 1 odds*" indicates that the runner will lose 20 times, and win 1 time, out of 21 races). Given that expected frequency formats appear to be more conducive to our type 1 processing, we would expect individuals' probability weighting of each runner's winning prospects to be fairly accurate under this mode, whether or not type 2 intervention is employed. The fractional odds format also informs gamblers that they will win *X* times their stake, should the horse win (i.e. if they bet $1 they would win $20). The same information, presented in *decimal returns format*, is written '*X*+1'; this figure representing the potential payoff (return) in units (including stake), based upon a one unit stake bet. Importantly, determining the likelihoods under this format is not oriented to type 1 processing. Specifically, in order to determine the probability of the horse winning, one must calculate the reciprocal of the decimal return, i.e. 1/(*X*+1).

Since the two information modes (fractional and decimal odds formats) are predicted to differ in respect of the degree to which they facilitate type 1 processing of the risks (i.e. the accuracy of type 1 assessment of probability), we can predict how prospect theory's weighting function may reflect this effect. The first hypothesis is that the most accurate perception of the runners' likelihoods should be made under fractional odds mode as this is in a relative frequency format. Therefore, I expect that the probability weighting function for this format should be relatively undistorted, with weightings which are likely to accurately reflect objective probabilities. However, the decimal returns format does not represent the likelihoods in a manner I expect to be easily interpreted by type 1 processing; specifically, because it requires the calculation of the reciprocals of the decimal return for a precise assessment. Therefore, I expect that the probability weighting function under decimal returns will be distorted to a greater degree compared to the fractional odds format.

By way of a further condition, I also consider a third price mode which is not currently used for horse-race odds but which may provide further insight into risk information modes. This is a *probabilities* mode, which explicitly provides the probability of a horse winning in a decimal format (e.g. .048, indicating a 4.8% winning chance). This format is essentially the counterpart to the decimal returns format, as the decimal return (payoff) can be calculated as follows: decimal return mode = 1/probability mode. Importantly, while the probabilities mode clearly emphasizes the likelihoods at the expense of the payoffs (in direct contrast to the decimal returns mode), this likelihood information is not presented in a relative frequency format. Therefore, I still expect that there will be a greater bias in the probability weighting function under the probabilities mode compared to the frequency format (fractional odds). These predictions are tested in experiment 2.

Method

Participants

One hundred and fifty undergraduate students, 65 female, 84 male, and 1 gender not-reported, between the ages of 19 and 41 (M =23.24 SD = 4.34), were recruited during a class, and were given course credits for their participation.

Design

A series of two-horse races were constructed. Two independent variables, both within-subjects, were employed. The first related to the magnitude of the differences in the winning probabilities of the favourite and the longshot. In particular, participants were presented with seven races, ranging from a race in which the winning chance of the favourite was close to that of the longshot, to one where the longshot was very unlikely to win. The second independent variable was the mode of representation of the information: odds, return, and probability format. Each of the seven races was presented using all three representation modes. The 21 different permutations of races which were employed in the study are presented in Table 3. All the races had an expected value of 1.

Procedure

Participants were given a booklet containing an introduction and consent form (see Appendix A for an example), information pages describing the types of information representations in simple terms, and details of the races. A debriefing form was provided on the final page, describing the nature of the experiment. The experiment was carried out in an experimental laboratory. Participants were asked to read the booklet and to record their decisions in the spaces provided. In order to minimize confusion, the information types were presented separately but were counterbalanced between participants. Before each group of races, a page described the subsequent information representation in detail using simple language. This approach helped to ensure that participants were clear about the meaning of each representation.

The order in which the items of information appeared was counterbalanced across the participants. Furthermore, the order in which the races appeared for each type of information was counterbalanced across all participants using a quasi-complete 7x7 Latin square. In order to exclude ordering effects, half of the participants received the information with the favourite presented above the longshot and the remainder received the information with the longshot presented first. Participants were asked to decide, for each race, on which horse they would place a hypothetical £1 bet, i.e. whether they would bet on the favourite or the longshot.

Table 3. Outline details of the seven races as presented in the three information modes used in experiment 2

		Three Information Modes			
Race	Runner	Fractional Odds	Decimal Returns	Probability of Winning	Difference between the runners' probabilities of winning
1	Favourite	4/5	£1.80	.555	0.12
	Longshot	5/4	£2.25	.444	-0.12
2	Favourite	4/6	£1.67	.600	0.20
	Longshot	6/4	£2.50	.400	-0.20
3	Favourite	1/2	£1.50	.667	0.34
	Longshot	2/1	£3.00	.333	-0.34
4	Favourite	4/9	£1.44	.692	0.38
	Longshot	9/4	£3.25	.308	-0.38
5	Favourite	1/4	£1.25	.800	0.60
	Longshot	4/1	£5.00	.200	-0.60
6	Favourite	1/9	£1.11	.900	0.80
	Longshot	9/1	£10.00	.100	-0.80
7	Favourite	1/20	£1.05	.952	0.90
	Longshot	20/1	£21.00	.048	-0.90

Expected value of each runner in each race = 1

Modelling

In order to test the hypotheses it was necessary to compare estimations for probability weighing functions under each of the three risk information modes. Consequently, I used the aggregate proportion of longshot choices made by the participants under each pricing format to estimate prospect theory models for each frame. The fitted weighting functions were compared with the predictions outlined above. To achieve this, as the choices between bets in a given race involved comparing two potential net gains, only two parameters were required: a γ value for estimating the average weighting function *w*, and an α value for estimating an average value function, *v*. The probability weighting function used to compare to the predictions is shown eq. 2, and the value function used in the fitting of the models (employed by Köbberling, 2002) was defined as follows:

$$v(x)\begin{cases} x^{\alpha} & if\ \alpha > 0 \\ \log(x) & if\ \alpha = 0 \\ 1-(1+x)^{\alpha} & if\ \alpha < 0 \end{cases} \qquad [5]$$

Based on the weighting and value functions, a perceived value, *V*, for runner *j* where *n* outcomes are possible (win or not win in this experiment), can be estimated as follows:

$$V_j = \sum_{i=1}^{n}\left[w_{ji}\left(p_{ji}\right)v_{ji}\left(x_{ji}\right)\right] \qquad [6]$$

Consequently, the subjective preference (P) for the longshot, *l*, over the favourite, *f*, can be estimated as follows:

$$P(l,f) = V_l - V_f \qquad [6]$$

Of course, some degree of random preference reversal ought to be expected. Indeed, as differences between prospects become harder to discern (i.e. in race 1), the probability of choosing the longshot over the favourite should near .5 (Luce, 1959). Accordingly, I estimated the proportion of longshot (cf. favourite) choices, *p*(*l*,*f*), as a standard logistic function of the magnitude of preference,

$$p(l,f) = 1/(1 + exp^{-(P(l,f))}) \qquad [7]$$

A grid search was performed to determine which combination of α and γ values resulted in the predicted proportion of longshots selected, *p*(*l*,*f*). This was achieved by best fitting (lowest root mean squared error of prediction, *RMSE*) the observed proportion of longshot choices in each of the pricing modes. The best fitting α parameters for the value functions for fractional odds, probabilities and decimal returns were, respectively, −0.609, 2.314 and 0.000. The best fitting γ parameters for the respective weighting functions were: 1.806, 3.549 and 0.489. These parameters were then used to plot weighting functions for each mode; these were compared to the predictions.

Results and Discussion

Figures 5a, b, and c show the proportion of longshot (cf. favourite) choices, *p*(*l*,*f*), made by the participants under each of the three risk information modes: fractional odds, decimal returns and probabilities. The related estimated average weighting functions are shown in Figures 5d, e, and f. The study employed a within subjects design. Consequently, the data was analysed using a repeated measures ANOVA[3]. Races were ordered by a categorical factor (race factor 1-7) based on the magnitude of the absolute difference between alternatives in terms of their winning probability (see Table 3). The results confirm that, in terms of the proportion of longshot choices, there was a significant interaction between the risk-information mode and the race factor, F (8.63, 708.02) = 8.30, $p < .001$. This suggests that a systematic reversal in stochastic dominance occurs, i.e. non-normative behaviour. The results also showed a main effect of risk-information mode on the number of longshot choices, $F(2, 164) = 13.06$, $p < .001$.

Figures 5d, e, and f, display the estimated weighting functions (based on the fitted prospect theory models) for the three pricing modes. It is clear from these figures that the weighting functions have different shapes. The degree of bias is indicated by the divergence of the solid line from the dotted line in Figure 5. As found in experiment 1, the mode which appeared to result in the least bias in weighting function was the fractional odds (i.e. least divergent from the straight dotted line). Whereas, the decimal returns format results in an overweighting of the longshots and underweighting of the favourites (a classic S-shaped function), and the probabilities mode results in a stronger underweighting of longshots than favourites.

It is evident from Figures 5 a, b and c that the three risk-information modes result in very different choice behaviours. The price formats which emphasize the risk (the fractional odds and probability modes) result in a decline in longshot (riskier) choices as the differences between the alternatives in terms of probability increase. In addition, as predicted, the decimal returns format, which emphasizes the payoffs (cf. risk), appears to result in a reversal of this stochastic dominance. Specifically, the same individuals appear to choose the riskier longshot (with higher payoff) more frequently as the difference in probabilities between the two alternatives increases. It seems likely that the overweighting, and hence choice preference towards the longshot in the decimal returns mode, may have resulted from some form of bias towards longshots' high returns. The reversal of this preference and underweighting of longshots under probability mode may, similarly, be due to a bias towards the favourite's high probability of winning.

[3] Mauchly's test indicated that the assumption of sphericity had been violated for the race independent measure, χ^2 (20) = 71.97, $p < .05$. Consequently, the degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .74$). The assumption of sphericity had not been violated for the mode or representation independent measure, χ^2 (2) =1.93, $p = .38$. For the interaction between race and mode, Mauchly's test indicated that the assumption of sphericity had been violated, χ^2 (77) = 160.53, $p < .05$. Consequently, the degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .72$).

The first two studies have demonstrated a degree of confluence between dual-process and prospect theory; a synthesis of these theories enabling better predictions and measurement of risky choice behaviour. However, these two studies have only focused on the probability weighting function. The next study focuses on the value function and the extent to which a synthesis of dual-process and prospect theories can better predict decisions evaluating investment performance, i.e. in a domain which is apparently well suited to prospect theory approaches.

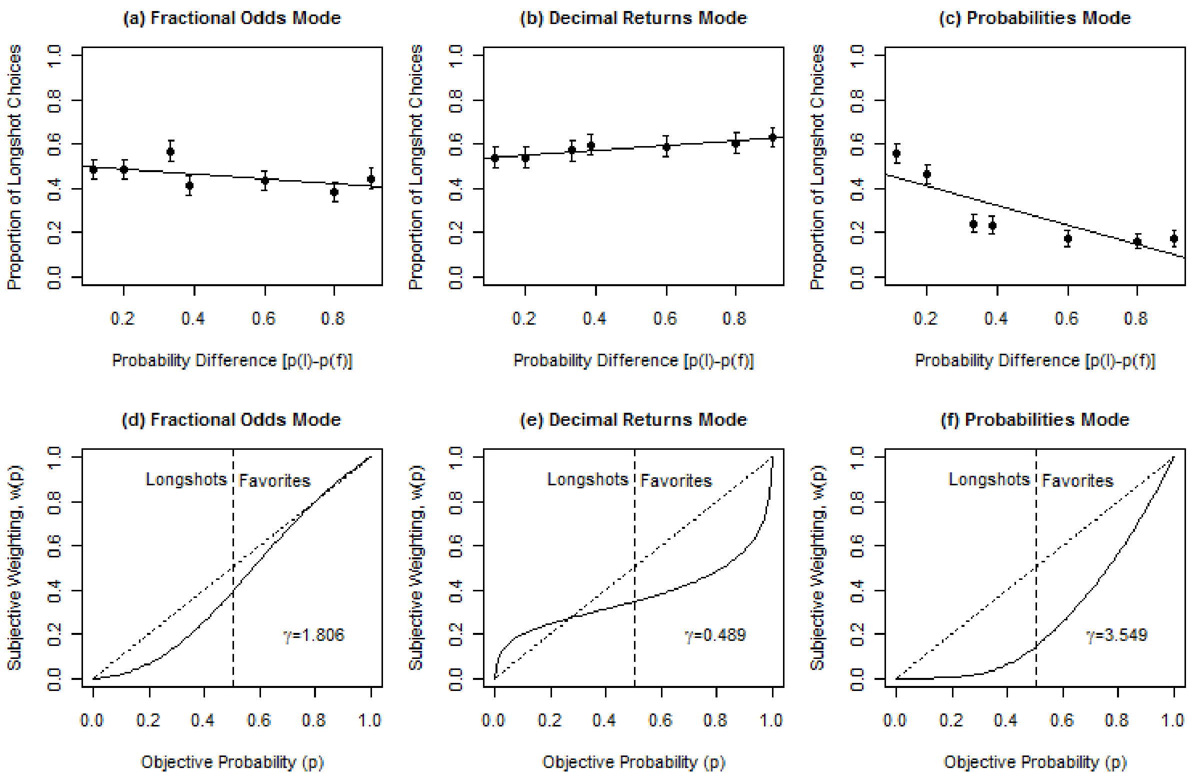

Figure 5. The proportion of longshots (cf. favourites) selected, with lines of best fit for (a)fractional odds (b) decimal returns and (c) probabilities price modes, and the impact of these modes on the weighting of favourites (p > .5) and longshots (p < .5) for (d) fractional odds (e) decimal returns and (f) probabilities.

Experiment 3

One of the most important aspects of prospect theory is the use of the loss aversion parameter. The parameter attempts to capture the robust funding that we tend to process losses and gains differently. According to prospect theory loss aversion heightens our sensitivity to changes in perceived value. As I discussed in the introduction, this loss aversion appears to be linked to type 1 processes and has been shown to have an emotional basis. However, while prospect theory has the loss aversion parameter, it does not capture other dual-processes that might be involved in the choice. In particular, the inputs into prospect theories formulae are the actual calculated changes in value. However, this chapter proposes that the individuals could also simply employ low-level magnitude heuristics (see Figure 1).

In this experiment, I consider whether prospect theory may be improved by allowing for the possibility of these low-level magnitude heuristics being used during bounded quantitative judgements. I consider the idea that type 1 magnitude processing might lead to a higher response to changes in values which traverse higher place-values (e.g., changes across 100s, in values ranging from 100-999) than equal changes at lower place-values (e.g., equal changes across 10s in values ranging from 100-999). I define this bounded quantitative heuristic, which I term the *place-value heuristic*, as follows: a difference between two numerical values is perceived to be greater in magnitude if the change results in a traversal at a higher unit place-value, than a difference which traverses lower unit place-values. For example, an increase in value from $490 to $500 might feel more significant at first glance than an increase from $480 to $490. This is hypothesized to arise from a greater type 1 response to a change at the hundred's (cf. ten's) place-value level. However, if higher level numeracy processing intervenes, by calculating the true percentage changes, it is in fact the second alternative that has increased by the most (2.08% compared to 2.04%).

The same could be possible for losses. Based on the place-value heuristic, a reduction in value from $500 to $490 might feel more significant at first glance than a reduction from $490 to $480, whereas the percentage changes indicate the opposite conclusion (-2.00% for the first but -2.04% for the second). So the first hypothesis is: if individuals use the place-value heuristic, they may make difference choices than would be expected if they used type 2 processing and the normative strategy of calculating the percentage changes.

Prospect theory, however, has more to say with respect to the above scenarios and in particular how it predicts the valuation of the losses compared the gains. Due to the loss aversion parameter in prospect theory, the percentage changes in value for losses may be perceived to be higher than the actual changes based on the normative strategy. To illustrate, I use prospect theory parameter values identified by Tversky and Kahneman (1992), i.e. α = .88, β = .88, λ = 2.25. As shown in Table 4, the absolute percentage gains for *a* and *b* are a marginally larger than the absolute percentage losses shown in *c* and *d*. Therefore, based on a normative assessment, the gains are marginally more significant. However, due to the exaggeration of the losses by in *c* and *d* by the loss aversion parameter, λ, the subjective valuation, $v(x)$, of *c* and *d* ought to be perceived as more significant than the gains of *a* and *b*. As the magnitude of the perceived difference between alternatives is usually found to impact on individuals ability to discriminate between choices (Luce, 1959, Fox & Poldrack, 2008; Luce, 1959; Busemeyer & Townsend, 1993), this loss aversion effect is likely to impact on the probability of individuals choosing each alternative. Thus, the second hypothesis is: individuals will be more likely to differentiate between choices in loss compared to gains situations due to this heightened sensitivity.

Table 4. Predictions derived from traditional prospect theory contrasted with those derived from synthesizing dual-process and prospect theories (via recoding the observed changes in investments using the place-value heuristic).

Observed change in investment	Traditional, change from reference point, inputs; x	Traditional prospect theory prediction; $v(x)$	Hundreds place-value heuristic for inputs; x	Synthesized dual process/prospect theory prediction, $v(x)$
a. \$480 to \$490	$x = 2.08$	$= x^{\propto}$, $= 2.08^{.88}$, $= \mathbf{1.905}$	$x = 0$	$= x^{\propto}$, $= 0^{.88}$, $= \mathbf{0}$
b. \$490 to \$500	$x = 2.04$	$= x^{\propto}$, $= 2.04^{.88}$, $= \mathbf{1.873}$	$x = 1$	$= x^{\propto}$, $= 1^{.88}$, $= \mathbf{1}$
c. \$490 to \$480	$x = -2.04$	$= -\lambda(-x)^{\beta}$, $= -2.25(-2.04)^{.88}$, $= \mathbf{-4.214}$	$x = 0$	$= -\lambda(-x)^{\beta}$, $= -2.25(0)^{.88}$, $= \mathbf{0}$
d. \$500 to \$490	$x = -2.00$	$= -\lambda(-x)^{\beta}$, $= -2.25(-2.00)^{.88}$, $= \mathbf{-4.141}$	$x = -1$	$= -\lambda(-x)^{\beta}$, $= -2.25(1)^{.88}$, $= \mathbf{-2.25}$

However, based on the dual-process concepts I described earlier it seems unlikely that individuals would actually calculate the relative differences in all instances (i.e. relying on type 2 processes). Rather, I expect that the loss aversion effect may be linked to other low level type 1 processes such as the use of the place-value heuristic I described above. Accordingly, I consider a synthesis of the place-value heuristic and prospect theories loss aversion parameter in an alternative model called the *synthesized prospect theory* model. Specifically, while the *traditional prospect theory* model uses "percentage change from a reference point" input *x*, the synthesised model replaces the input, *x*, with the number of high-place value traversals. As shown in table 4, while traditional prospect theory would order a > b and d > c, the synthesized model would order b > a and c > d due to this change in inputs. Note, however, that the loss aversion parameter plays a role in subjective values for both these models when compared to the normative model. Accordingly, the third hypothesis is: loss aversion may be associated with the use of place-value heuristics - i.e. if the place-value heuristic is used, then this effect ought to be strongest in loss versus gain scenarios. These hypotheses were tested in the following experiment.

Method

This experiment compared three models (1) a *normative model (NRM)* based on only the percentage change of values, (2) a *traditional prospect theory (TPT)* model which retains this “relative change from a reference point” input but which also considers the role of affective processing in the form of sensitivity to losses, and (3) a bounded quantitative judgement model, *synthesized prospect theory*, which retains this loss-sensitivity concept but rejects the assumption of higher-level calculations as inputs into the model, replacing them with low-level magnitude processing inputs in the form of the place-value heuristic.

Participants

Ninety-three participants were recruited during a break in class. The mean age was 23.98 (SD = 3.71) and there were 49 female and 44 male participants.

Design and Procedure

Participants were undergraduate students at the University of Southampton rewarded with course credits. The experiment was carried out in an experimental laboratory. They were given an information and consent form prior to each task (see appendix A for an example) and were fully debriefed after the experiment. In total there were twelve binary choices, six involved judging gains and six involved judging losses (see Table 5). Each of the choices had the same absolute change in value of +/- 2,204. However, as shown in table 5, the place values traversals were counterbalanced with the percentage changes such that the percentage changes would be congruent and incongruent with the place-value heuristic choices across both gain and loss situations. To eliminate ordering effects, a 12 × 12 latin square design was used resulting in 12 different orders of the questions whereby each of the questions appeared in each serial position only once.

Table 5. The twelve binary choices offered to participants with the mathematically optimal choice (Relative Difference) the Rational Prospect Theory predictions (TPT), and the synthesis of the place-value heuristic with prospect theory (SPT) predictions.

Set	Stock	Original Value (n-1)	Present Value (n)	Normative Theory (NRM)	NRM Choice	Traditional Prospect Theory (TPT)	TPT Choice	Place-value heuristic	Synthesized Prospect Theory (SPT)	SPT Choice	Congruency between NRM/TPT and SPT
1	A	17,911	20,115	0.123	B > A	0.1582	B > A	3	2.63	A > B	Incongruent
	B	17,098	19,302	0.129		0.1648		2	1.84		
2	A	17,010	14,806	-0.130	B > A	-0.3726	B > A	-3	-5.92	B > A	Congruent (B)
	B	17,901	15,697	-0.123		-0.3562		-2	-4.14		
3	A	18,089	20,293	0.122	B > A	0.1569	B > A	2	1.84	B > A	Congruent (B)
	B	17,900	20,104	0.123		0.1583		3	2.63		
4	A	17,908	15,704	-0.123	B > A	-0.3561	B > A	-2	-4.14	A > B	Incongruent
	B	18,004	15,800	-0.122		-0.3544		-3	-5.92		
5	A	97,904	100,108	0.023	B > A	0.0355	B > A	3	2.63	A > B	Incongruent
	B	97,098	99,302	0.023		0.0358		2	1.84		
6	A	102,911	100,707	-0.021	A > B	-0.0764	A > B	-2	-4.14	A > B	Congruent (A)
	B	102,001	99,797	-0.022		-0.0770		-3	-5.92		
7	A	96,902	99,106	0.023	A > B	0.0358	A > B	3	2.63	A > B	Congruent (A)
	B	97,030	99,234	0.023		0.0358		2	1.84		
8	A	101,903	99,699	-0.022	B > A	-0.0771	B > A	-2	-4.14	A > B	Incongruent
	B	102,030	99,826	-0.022		-0.0770		-3	-5.92		
9	A	7,098	9,302	0.311	A > B	0.3573	A > B	2	1.84	B > A	Incongruent (A)
	B	7,911	10,115	0.279		0.3248		3	2.63		
10	A	10,001	7,797	-0.220	B > A	-0.5945	B > A	-3	-5.92	B > A	Congruent (B)
	B	10,911	8,707	-0.202		-0.5507		-2	-4.14		
11	A	7,098	9,302	0.311	B > A	0.3573	B > A	2	1.84	B > A	Congruent
	B	6,911	9,115	0.319		0.3658		3	2.63		
12	A	12,001	9,797	-0.184	A > B	-0.5064	A > B	-3	-5.92	B > A	Incongruent
	B	11,911	9,707	-0.185		-0.5098		-2	-4.14		

Models

The normative model (NRM) is simply based on the relative difference in the prospects. It will always choose the gaining prospect that has the largest relative gain and the losing prospect with the smallest relative loss. The relative difference (*r*) was calculated as following, whereby x_n is the current value of the stocks and x_{n-1} was the original value,

$$r(x) = (x_n - x_{n-1}) / \max(x_n, x_{n-1}) . \quad [8]$$

A probabilistic prediction is determined as follows: the probability of choosing A over B, $P(A,B)$, is predicted by

$$P(A,B) = F(d_N) = F(r(A) - r(B)) , \quad [9]$$

where F is a function (see below) of the difference between the alternatives in their objective relative changes in value (see Luce, 1959, Fox & Poldrack, 2008; Luce, 1959; Busemeyer & Townsend, 1993). Note that for a deterministic prediction, A would be chosen when $d_N > 0$, B is chosen when $d_N < 0$.

The traditional prospect theory (TPT) model makes the same deterministic predictions as the normative model. However, the loss aversion parameter in the model means that it predicts stronger preferences in loss, compare to gain, situations as the loss aversion parameter heightens perceptual sensitivity. The value functions for gains and losses for the traditional model are, v_T, is as follows (where α = .88, β = .88, λ = 2.25):

$$v_T(x) = r(x)^{\alpha} \text{, in gain scenarios,} \quad [10]$$

$$v_T(x) = -\lambda(-r(x))^{\beta} \text{, in loss scenarios.} \quad [11]$$

$$\text{Thus, } P(A,B) = F(d_T) = F(v_T(A) - v_T(B)) \quad [12]$$

For the synthesized prospect theory (SPT) model, the inputs are not the relative difference between alternatives but rather the number of high place value traversals *t* made by the prospect *x*. Thus, the value function under the synthesized model, v_S, is as follows:

$$v_S(x) = t(x)^{\alpha} \text{, in gain scenarios,} \quad [13]$$

$$v_S(x) = -\lambda(-t(x))^{\beta} \text{, in loss scenarios,} \quad [14]$$

$$\text{Thus, } P(A,B) = F(d_S) = F(v_S(A) - v_S(B)) . \quad [15]$$

Again, as a deterministic prediction, A would be chosen when $d_S > 0$ and B is chosen when $d_S < 0$.

The three models (NRM, TPT, and SPT) aimed to predict the likelihood that A would be chosen over B based on the perceived difference d_X which was different for each model (d_N, d_T, or d_S). As our participants each answered 12 questions (a within-subjects design) there was the possibility of correlation within participants across questions. This was controlled for by using a linear mixed model methodology which allowed the participant to be a random variable entering on the intercept. The probability of choosing A over B was predicted as follows.

$$P(A,B) = F(d_X) = f[\alpha_j + \beta(d_{X\,ij}) + \varepsilon_{ij}], \quad [16]$$

$$\alpha_j = \alpha + p_j\,. \quad [17]$$

where the intercept α can vary depending on the participant p_j resulting in the random intercept α_j, the coefficient β acts on the difference function, d specified by model X, (where X may be N for the NRM model, T for the TPT model, and S for the SPT model), for question i. The function f is a standard binomial function on this linear term.

Results and Discussion

Having fitted each of the three probabilistic models they were compared based on log-likelihood tests (see Table 6). The intercept model simply assumes that the best prediction of the data is the intercept, or aggregate mean percentage of '*A*' choices. This is the null hypothesis that none of the experimental manipulations have an effect with individuals choosing A over B at a constant rate across each condition. The NRM model is compared based on improvements in Log Likelihood (LogLik) and finds that the NRM model does not significantly improve on this null hypothesis model. This suggests that the percentage change in prospects is not a significant predictor of choices overall and that participants are therefore, not behaving in accordance with this normative strategy.

Table 6. Chi Squared Model Selection Tests. NRM indicates the normative model, TPT is the traditional prospect theory model, and SPT is the synthesis of prospect theory and the place-value heuristic. Chi Squared (Chisq) tests evaluate the current model against the mode from the previous row for significant decreases in Log Likelihood (LogLik).

Model	Df	AIC	BIC	LogLik	Chisq	Sig
intercept	2	1546.4	1556.4	-771.19	-	-
NRM	3	1546.5	1561.6	-770.26	1.8725	0.1712
TPT	3	1541.4	1556.5	-767.71	5.0902	< 2.2e-16 ***
SPT	3	1523.7	1538.8	-758.86	17.692	< 2.2e-16 ***

However, the results in Table 6 do show that traditional prospect theory model (TPT) can more accurately predict the probability of choosing A over B than the normative, NRM, model. As the only difference between the NRM and the TPT models is the use of a loss aversion coefficient in the model (λ) which results in a greater perceptual sensitivity to losses compared to gains, this indicates that loss aversion is important in predicting choice behaviour. This supports the traditional prospect theory concept of loss aversion impact on perceptual sensitivity towards gains versus losses. Essentially, while the relative change overall does not significantly predict choices, when the percentage change is linked to prospect theories loss aversion coefficient choices are better accounted for.

More importantly, however, was the finding that the synthesised model, SPT, was an even better predictor than the traditional prospect theory model. This indicates that while loss aversion is important in predicting the results, the place-value heuristic inputs are a stronger predictor of choices than the relative change in value inputs. This suggests that both the place-value heuristic (a dual-process theory factor) and loss aversion (a prospect theory factor) are both important when attempting to account for choices. In order to find out where this effect lies, Figure 6 shows the percentage of A choices made by participants under the congruency and gain/loss conditions.

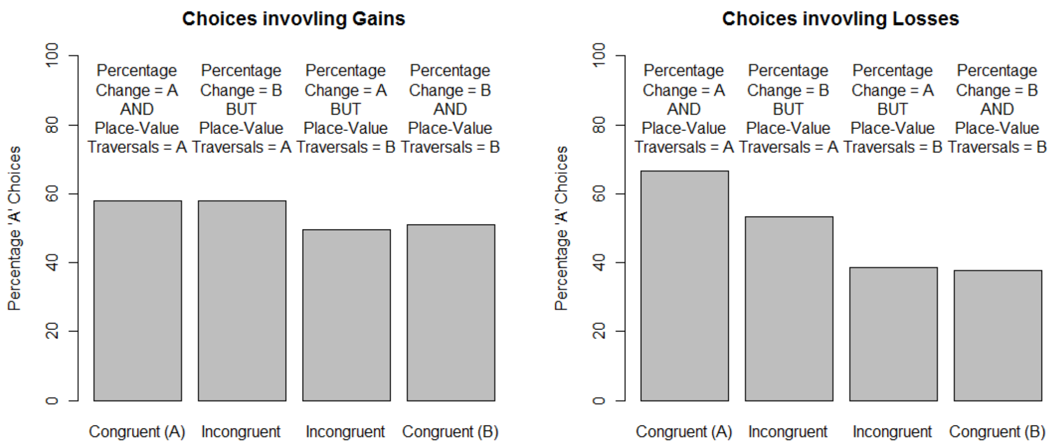

Figure 6. Percentage of A choices under each 2 × 2 congruency conditions of the actual percentage change and the number of place value traversals for gains and losses.

Figure 6 shows why the synthesized model was the better predictor as the place-value shows a greater effect on choices than the relative change. Furthermore, the effect of place-value heuristic appears to be greater in the loss than in the gain situations. This reveals why it is that the synthesis of the place-value heuristic combined with prospect theories loss aversion parameter was the best account of choices. Also, note that overall there appears to be a congruency effect in losses whereby there is a stronger effect on choices when type 1 processing (in the form of the percentage change) and the type 2 processing (in the form of the place-value heuristic) are congruent than when they are incongruent, but that this is only observed in the choices involving losses.

This study demonstrates that low-level magnitude processes such as the place can be better predictors of choices than assuming the use of higher-level calculations. Furthermore, while prospect theory can improve our prediction over normative models due to its ability to model the impact of the loss aversion on sensitivity to changes, its weakness is that it relies on assumptions of higher-level calculations falling into the "*cognitive and consequentialist*" trap discussed in the introduction to this chapter. When some of the principles of prospect theory (sensitivity to losses) are combined with dual-process ideas such as low-level magnitude heuristics, the results show that predictions of choices can be greatly improved.

General Discussion

The aim of this article was to improve our understanding of contextual biases in the evaluation of numerical information. I attempted to achieve this via a synthesis of dual-process concepts and prospect theory. The predictions based on this synthesized approach were shown to be effective predictors of the effects of contextual biases on judgements and decisions concerning numerical information. In particular, I believe the approach provides an effective means of better understanding the nature and characteristics of bounded quantitative judgements.

The first experiment employed a combination of dual-process theory and a traditional S-shaped probability weighting function from prospect theory to predict the perceived strength of forensic evidence under different risk-information modes (under "match" *vs*. "not-match" frames). It was revealed that individuals were more likely to be influenced by the type of risk information mode in "match" frames than in "non-match frames". This was hypothesized to result from a greater use of type 2 processing when faced with "non-match" framed information. The effect of the risk information modes in the "match" (cf., "non-match") frame was consistent with the idea that probabilistic information presented as percentages is less effectively processed by type 1 processing than as relative frequency format. In particular, the reduction in guilty verdicts under the percentage (cf. relative frequency) formats was consistent with the underweighting of high probabilities attributed to prospect theory's S-shaped probability weighting curve. This clearly has important implications for the recent adoption of probabilistic evidence in court and how contextual factors, such as information modes and frames, can have a significant effect on individuals' perceptions of the strength of forensic evidence and ultimately on their guilty/innocent judgements.

The second experiment, associated with a betting task, assess the role of risk information modes in more detail measuring the impact on the estimated weighting functions in prospect theory. Dual-process theory was able to predict the nature of fitted prospect theory probability weighting functions which indicated that the least distorted weighting of probabilities was, again, under a relative frequency format (fractional odds mode). The weighting function under decimal returns mode was distorted following the classic S-shaped prospect theory probability weighting function. The third type of odds format, which explicitly presented the probabilities (probabilities mode), resulted in a greater distortion in the weighting function compared to that induced by the relative frequency format. Overall, these distortions in the perception of the alternatives resulted in preference reversal and reversal of stochastic dominance such that riskier alternatives were preferred under decimal returns format, and safer alternatives were preferred under fractional odds and probabilities format. I interpret this effect as evidence of a bias brought about by the modes: decimal returns result in a bias towards the longshot (highest paying), whereas the probabilities mode results in a bias towards the favourite (lowest risk).

The third experiment considered how the dual-process inspired idea of a low-level numerical processing, the place-value heuristic, could be integrated with prospect theory's value weighting function to predict overreaction to changes in investment value. The results showed that participants were more sensitive to changes in high place-value than in percentage changes in value and that this effect was most strongly observed in loss scenarios. Accordingly, the synthesized prospect theory model was superior to the traditional prospect theory model or the normative model. This finding has clear implications for understanding overreaction in market behaviour, especially in times of falling market prices.

The fundamental aspect of the dual-process theory employed in these studies was default-interventionism, the idea that our deliberation process evolves over time depending on assessments against the satisficing principle (Evans, 2007a). Initially, our default process in handling numbers tends to be heuristic, involving type 1 processing (low-level magnitude heuristics). This, I believe, is important in resulting in the value and weighting functions observed in the fitting of prospect theory functions. If the decision-maker perceives that this initial, heuristic, mental model is not sufficiently effective or that the task requires a more careful and calculative approach. The latter approach is more time consuming but produces more precise calculations which may have the effect of removing the biasing effects of presentational formats and perhaps reducing or eliminating the distortions displayed in prospect theory's value or weighting functions.

Support for the idea that type 2 processing can be used to remove contextual biases in numerical processing is found in a set of experiments performed by Peters, Västfjäll, Slovic, Metz, Mazzocco, and Dickert (2006). The studies compared individuals with different levels of numeracy (type 2 processing ability: determined by scores in a probability test), on common framing/mode tasks. The results demonstrated that individuals with high (cf. low) numeracy tended to retrieve and use appropriate numerical principles and thus were better able to remove contextual biases. This fits with the default-interventionism idea of the dual-process framework in which those individuals that can employ effective higher level numerical processes should be better able to override the effects of task-irrelevant features.

Further evidence in support of the dual-process approach to gain/loss framing is found in studies of brain activation. Gonzalez, Dana, Koshino, and Just (2005) employed brain activation functional magnetic resonance imaging (fMRI) to reveal that different frames resulted in different levels of cognitive effort (measured by brain activation). This, in turn, mediated the likelihood that a participant would calculate expected values (higher-level calculations) or would simply rely on emotional (type 1) heuristics. This finding is exactly as would be expected based on the dual-process model shown in Figure 2.

In conclusion, a wide variety of real-world decisions regarding numerical information may be made under contextual bias, and this study has demonstrated how a synthesis of the theory of cognitive processes (dual-process theory) and static-economic models of choice (prospect theory) can offer a powerful approach for predicting choice behaviour. In contrast to relying purely on "*cognitive and consequentialist*" models that only employ "*expectation-based calculus to arrive at decisions*" (Loewenstein, Weber, and Hsee, 2001), this synthesized approach proved useful in three diverse tasks derived from three different real-world domains.

In the domain of JDM, dual-processes are often neglected in the literature in favour of quantitative-economic approaches such as prospect theory (Evans, 2007a). It is hoped that the synthesized approach outlined in this study may go some way towards a more encompassing theoretical approach to decision analysis. Finally, it is hoped that the consideration of dual-processes may further extend the recent interest into how we may enhance individuals' ability to employ numerical information (Peters, Dieckmann, Västfjäll, Metz, Slovic & Hibbard, 2009) to improve their decision-making.

Summary Points

- Dual-process theory has much to offer quantitative JDM modelling; both in explaining why certain functions are required to account for choices as well as in developing new, more effective, quantitative models of decision behaviour.
- Far from considering dual-process theory and prospect theory in isolation, I aimed to demonstrate the benefits of a synthesized approach to decision-analysis.

- Based on this study, I conclude that dual-process theory combined with quantitative approaches to decision modelling may be useful in exploring the role of early information biases.

Chapter III – Literature Review and Model Simulations

"Nothing is more difficult, and therefore more precious, than to be able to decide."
- Napoleon Bonaparte (1769 - 1821)

Introduction

Chapter I sought to introduce the topic of early-informational biases during JDM and a potentially useful dual-process theory concept; *default-interventionism*. Chapter II considered how a default-interventionist view of numerical processing and the static-quantitative model, prospect theory, may be synthesized to account for the role of contextual biases in risky decisions involving numerical information. An important finding was a synergistic effect whereby behaviour could be best predicted by a dual-process account combined with prospect theory.

The experiments clearly demonstrated that dual-process concepts have much to offer JDM research, particularly with respect to developing more effective quantitative models. However, while Chapter II did indicate that a dual-processes and quantitative JDM models can work together, prospect theory demonstrated some limitations for modelling early-informational biases. For example, prospect theory could predict the nature and characteristics of certain biases but could not predict when the biases should/should not be observed. For this the consideration of dual-processes was required. Prospect theory could be used to predict and measure the nature of some of the processes (e.g. relative frequency versus probability modes) but it failed to predict others (e.g. the use of the place-value heuristic). Furthermore, it could not predict the removal of the bias effects due to type 2 intervention as shown in the "non-match" condition in experiment 1. Also, given that default-interventionism is strongly tied to the temporal differences between the rapid type 1 processes and the slow type 2 processes, I feel that the static modelling approach is likely to be limited in its capacity for representing some of the most important aspects of default-interventionism.

Based on this initial conclusion, in this chapter, I examine the dual-process theory literature in more detail with particular interest paid to the recent theories regarding the mediation of default-interventionism. Based on this literature I depart from a static-oriented modelling approach, and instead focus on dynamic modelling techniques. Thus, while the previous chapter used dual-processes to adapt prospect theory (a deconstructive approach by my definition), this chapter considers how it might be possible to build a dynamic model based on dual-process principles (a constructive approach by my definition).

The Satisficing Principle: A Third Type?

As discussed in the introduction, the dual-process mechanism that seems most relevant to the focus of this thesis is default-interventionism. Under default-interventionism, individuals form early impressions based on type 1 processes and the involvement of this early information in the final judgement has something to do with the satisficing principle (Evans, 2007a) and the intervention of type 2 processes.

According to the satisficing principle, the influence of early, type 1, responses may depend on whether an individual judges the early response is sufficient to form a judgement or make a decision. For this to be true there must be some degree of assessment made by a monitoring system which forms this satisficing judgement. Thompson (2009) proposes that the assessment of the initial type 1 response may be triggered by a '*feeling of rightness*' that is processed in parallel with the content of the type 1 process. Indeed, recently it has been suggested that we may be required to account for a third type of processing (type 3 processing) which is concerned with resolving the conflict between both type 1 and type 2 responses (Evans, 2009) and relates to individuals' cognitive styles (Stanovich, 2011). On this basis, Stanovich (2011) has presented a tripartite development of the dual-process account. System 1 remains the same as the original dual-process theory, often referred to as the TASS (*the autonomic set of sub-systems*). The proposal was that system 2 should be separated into two sub-systems: the *algorithmic* and the *reflective* systems. The *algorithmic* system is much closer to the traditional set of systems involved in type 2 responses; performing hypothetical thinking, abstract logical reasoning, higher-level quantitative calculations, etc. The *reflective* system represents the monitoring system (type 3 processing) which evaluates an individual's judgements according to the satisficing principle.

Stanovich (2011) based his proposal, in part, on some important problems he observed with tests of executive functioning and other traditional intelligence or aptitude tests. His central argument was that these tests measure the algorithmic system but not the reflective system. In traditional intelligence tests, the performance level is dictated by the test which generally attempts to detect the limits of an individual's algorithmic thinking ability. Differences in the efficiency (some tasks are measured by response time) and effectiveness (e.g. whether mistakes were made or not) of the algorithmic system strategies employed by candidates represents the variation in their performance. However, in the real world, the performance level is usually self-defined. Individuals may not extend to the limits of their algorithmic thinking ability due to '*cognitive miserliness*'. Thus, individuals may perform below their maximum potential in real world tasks due to the employment of the satisficing principle. Indeed, Stanovich (2011) describes how individuals with high scores in intelligence tests (i.e. high algorithmic thinking abilities) are not necessarily immune from type 1 biases in experiments. According to his theory, these biases are not the result of a lack of effective tools, what Stanovich (2011) refers to as *mindwear*, as they are individuals with high algorithmic thinking abilities. Rather, the biases are due to a lack of motivation to use them. The reflective system therefore determines whether the individual will be a cognitive miser or not, i.e. whether the individual will tend towards more rational, careful, thinking or more 'quick-and-dirty' heuristics[4].

The concept of a third type of processing also reflects the large amount of literature regarding thinking dispositions (Stanovich & West, 1997). For example, some individuals tend to have a greater *need for cognition* than others (see Cacioppo, Petty, Feinstein, & Jarvis, 1996). In accordance with Stanovich's (2010) argument that general intelligence measures tap a different cognitive system to the systems relating to the satisficing principle, the relationship between a desire for a conclusive answer and intelligence has been observed to be non-significant (r = -.17; Kruglanski & Webster, 1996). Furthermore, while individuals can differ in their cognitive miserliness based on personality differences (such as a need for cognition), as outlined in the introduction, motivated reasoning research also reveals that individuals can adapt their thinking in different situations due to external pressures or motivations.

All these ideas are critical to the investigation into the role of early information as it appears as though individuals have the ability to employ the third type of processing to determine whether they will be more or less cognitively miserly in different situations. The general idea is that when an individual constrains their cognition they will rely on the early information from type 1 processing. Those that are motivated to cognize more carefully about a problem may rely less on the early information and instead employ more careful reasoning using the type 2 processing.

Strategy-Oriented versus Criteria-Oriented Decision Theories

In introducing a third type of processing, this new tripartite model differs in a subtle way to the traditional conceptualization of bounded decision-making in other JDM theories. Adaptive JDM behaviour refers to the concept of employing different decision strategies based on motivational and stress reasons. The cost/benefit approach (Beach & Mitchell, 1978; Payne, Bettman, & Johnson, 1988) which argues that individuals trade off accuracy and cognitive effort. The stress approach (Janis & Mann, 1977) proposes that environmental

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[4] Note that, as pointed out by Evans (2009), while the term '*heuristics*' could be applied to type 1 responses it could also refer to a '*rule which is consciously learnt and applied*' (Evans, 2009, *p*.36), i.e. type 2 processes can also be heuristic.

pressure induces stress which in turn forces individuals to switch strategy. Finally, the evolutionary approach (Gigerenzer & Todd, 1999), argues that individuals tend to prefer the fastest and most frugal strategy and adapt according to the environment and context of the decision. All these theories propose that there is only one aspect to adaptive decision-making processes, and that is that individuals change the *strategy* they employ. For example, Payne, Bettman & Johnson's (1993) adaptive decision-maker theory argues that individuals may select from a variety of strategies to make judgements and choices. These strategies are seen as a "toolbox" of strategies each of which may vary in terms of speed-accuracy tradeoff criteria. For example, there are models of simple heuristic processes, such as *take-the-best* (TTB) which reflects the employment of a simple rule of thumb, such as relying on one attribute seen to be a reasonably valid indicator (Gigerenzer & Goldstein, 1996). At the other end of the scale, there are more complex models which would require extensive type 2 processing to arrive at a solution such as weighted-additive rules and lexicographic ordering rules. For example, the *weighted-additive-rule* (WADD) is a compuationally costly strategy whereby all relevant attributes for each alternative are weighted for importance and then summed and the highest valued alternative is selected (Payne, Bettman, & Johnson, 1993).

The difference between this toolbox approach and the default-interventionist approach is the role of type 3 processes in each. Under a toolbox approach, it is unclear as to howt the agent is expected to select a satisyficing strategy for the task prior to performing any judgement behaviour. Indeed it is often assumed that when we observe an individual making a judgement, then they must have chosen a strategy *a priori* and are simply then enacting it. For more details on the adaptive decision-maker theory refer to Payne, Bettman, and Johnson (1988, 1993). However, the role of type 1 processing is not clear in this account. If a type 1 reponse is considered to be just another type of "strategy" from the toolbox, the the theory implies that type 1 processing can only be employed if it is assessed to have been strategically more appropriate than for the decision being made. This clearly does not capture the automaticity of type 1 processes and such a theory of type 1 processing falls into the "*cognitive and consequentialist*" trap discussed earlier.

The default-interventionist approach outlined in Chapter I differs from this strategic-oriented view of bounded rationality. Instead of allocating type 1 processes via strategic thinking, individuals default to more type 1 driven responses if they are available to make the decision, and subsequent strategic behaviour is enacted in an interventionist capacity depending on an ongoing and iterative assessment based on the satisficing principle (see Figure 1 in Chapter I). Thus, the final "strategy" that we observe in an individual's choice behaviour (e.g. a quick heursitic response versus a slow analysis) need not be clearly defined and selected at the outset (a pre-emptive conflict model), but may rather be the *product* of the point at which type 3 processing deems the judgement to be satsifycing. This resolves the rather difficult problem, seemingly ignored by the adaptive decision-maker theorists, regarding how the appropriate strategies can be selected *a priori*. Simply, the so called "decision strategy" does not have to be always selected from the outset from a toolbox. Rather, an adaptive strategy may be employed which begins more type 1 and heuristic-orientated and evovles into a more type 2 and anlytic-oriented strategy during the course of the decision. The evovling deliberation is assessed iteratively against some statisficing criterion during the course of the decision only stopping the deliberation process once the statisficing criterion is met (See Figure 1 in Chapter 1). Accordingly, in contrast to the toolbox approach, the strategy does not necessarily define the judgement criteria. Rather, the criteria – the point at which the judgement is deemed satsifycing – determines the extent of the strategy that ends up being employed.

If decision-making strategies do indeed follow this default-interventionist approach, the modulation of type 1 responses versus subsequent type 2 responses requires a criterion-oriented, rather than strategy-oriented, mechanism. I define this criterion as some measure of the current mental model based on a satisficing assessment made by a third type of processing. The question remains as to how best to model this type 3 processing as a criterion-dependent mechanism in a quantitative model.

Sequential Sample Models and Four Default-Interventionism Characteristics

Four Characteristics

As discussed in the beginning of this chapter, I consider how one might be able to draw more concrete links between the quantitative JDM approaches and dual-process theory. In doing so I considered that a criterion-oriented, rather than strategy-oriented mechanism better represents default-interventionism, particularly with regards to the notion of a third system (type 3 processing). Based on this literature, I outline four key default-interventionist principles (see Table 1) that I believe would be important in capturing this view of adaptive decision-making. Note that there are many other aspects of dual-process literature that are not captured in Table 1. However, I consider these four aspects to be most relevant to the goal of developing an initial quantitative model for understanding early versus late information JDM. The successes and limitations of a simplistic quantitative model based on these features will form the basis of the rest of this thesis and serves as a starting point for future research. I shall return to these limitations and future directions in Chapter VII.

Table 1. The four default-interventionist characteristics that I shall attempt to capture in a criterion-oriented dynamic decision model

Characteristic	**Description**
(1) Dynamic	The model must be dynamic (rather than static) in order to capture default-interventionism; i.e. the idea that early type 1 processing tends to occur in the first instance and is then followed by subsequent type 2 processing as required.
(2) Type 1 Default Response	Type 1 response should be rapid, automatic, and default
(3) Type 2 Intervention	Type 2 processing should be slow, effortful, time consuming, and subsequent to the type 1 response
(4) Type 3 Processing - Satisficing Principle	The impact of type 1 and type 2 processing will be determined by a satisficing criterion mechanism (type 3 processing), rather than *a priori* selection.

Sequential Sample Models

In the domain of mathematical psychology, there are dynamic-quantitative models termed *sequential sample models* which are derived from models of memory, perception, and categorisation (Link & Heath, 1975; Nosofsky & Pameri, 1997; Ratcliff, 1978; Ratcliff & Smith, 2004; Vickers, 1979). I believe that these models may be useful for capturing the four elements described in Table 1.

The basic premise is that our ability to perceive differences and distinguish stimuli from noise depends on whether the perceived stimulus can elicit a strong enough response to pass the criterion threshold and trigger a response. Considering a two-choice decision (*A* or *B*), sequential sample models propose that individuals will attend to attributes or cues relating to the decision and that this elicits a valence value, e.g., $V_A(n) - V_B(n)$ (Busemeyer & Townsend, 1993), in the decision maker's mind. This random variable represents a singular evaluation of one aspect of the choice problem at a specific point in time resulting in a momentary bias towards one choice over another. This sample, *n*, constitutes just one of the many samples taken during deliberation.

The decision maker will then consider other aspects of the choice problem in a sequential manner, each time forming valence values. The sum, at a particular point in time, of all these individual samples from the choice problem defines the accumulated preference (*P*) state at that time. A positive value, $P > 0$, indicates a momentary bias towards the positive threshold, say choice *A*, and a negative value, $P < 0$, indicates a momentary bias towards the alternative, say choice *B*. As more valences are gathered over time, the preference state fluctuates over time; sometimes in favour of choice *A* and at other times in favour of choice *B*. Busemeyer and Townsend (1993) describe a basic process of the accumulation of valence states into changing preferences.

$$\text{Initial preference state, } P(1) = [V_A(1) - V_B(1)], \quad [1a]$$

$$\text{Second preference state, } P(2) = P(1) + [V_A(2) - V_B(2)], \quad [1b]$$

$$n\text{th preference state, } P(n) = P(n\text{-}1) + [V_A(n) - V_B(n)], \quad [1c]$$

To summarise the overall effect across individuals and within an individual across different trials, these numerous samples of valence are accumulated in a random walk fashion resulting in an average drift which defines the general direction and velocity of the accumulation and overall preference. This drift occurs until the accumulation reaches a threshold, θ, which ends the deliberation and a choice is made (for a more detailed explanation, see Albert, Aschenbrenner, & Schmalhofer, 1988; Aschenbrenner, Albert, & Schmalhofer, 1984; Busemeyer & Townsend, 1993; Diederich, 1997; Diederich, 2003; Wallsten & Barton, 1982).

Figure 1 shows a depiction of a random walk in which an individual's preference varies over time fluctuating between choices *A* and *B* until finally the preference state reaches a threshold. Presumably, the individual first considers some aspects in favour of choice A and then considers some positive aspects of *B* over *A*. Finally, a strong attribute in favour of A is enough to accumulate the preference state past the decision threshold for *A*. The arrow shows the general drift direction which defines the average time taken to choose and the probability that *A* will be chosen over *B*. For the purposes of this review the discussion will be restricted to three critical elements from these models; the general change in preference state over time (*drift*), the *threshold*, and the *initial preference state*. Although this will allow a broad discussion of the general nature of the models, it should be noted that most of these sequential sample models are considerably more complex (e.g., Busemeyer & Townsend, 1993).

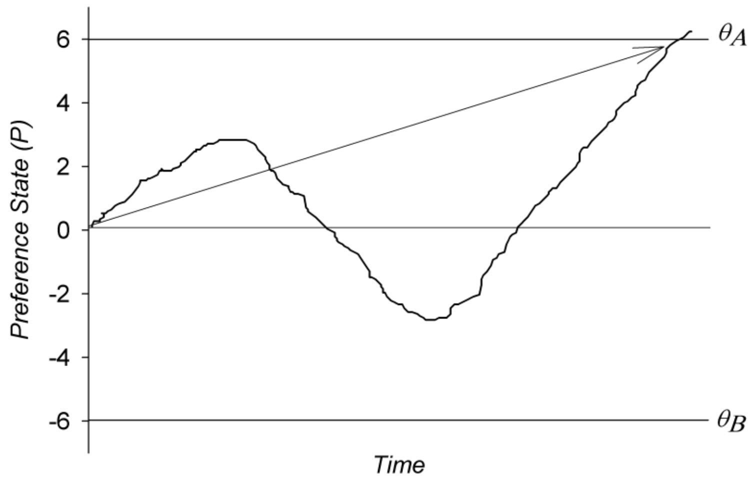

Figure 1. A depiction of a sequential sample decision in which preference state fluctuates between choice alternatives and cues are considered and a choice is made once the accumulation reaches one of the thresholds; in this case, choice A.

Drift

The drift represents the mean path traced by the preference state across trials and individuals and is normally distributed with mean (ζ) and variance (s^2), also referred to as the *diffusion coefficient* (Ratcliff & Smith, 2004). Due to the variability of the drift during evidence accumulation, the same drift rate may pass the threshold at different times and may pass the wrong threshold simply due to chance. If the drift is strong (i.e. low variance and high mean), the chances of the drift passing the correct threshold (defined as being congruent with the mean drift rate) is higher than if the drift is weak (i.e. high variance and/or low mean). As the model is dynamic, the drift not only determines the probability that an alternative will be chosen but also the deliberation time. For a difficult decision in which alternatives are very similar, it will take longer as each sample of valence will be small resulting in a slower drift. In contrast, for an easy choice when one option is obviously better than the alternatives, the decision time is much quicker as the faster drift reaches the threshold at a quicker rate. For example, Diederich (2003) revealed how such a model can accurately predict deliberation time as choice conflict increases. Finally, due to the geometry of the process, the models correctly predict that the distributions of deliberation times are right skewed (Ratcliff & Smith, 2004). Furthermore, note that this refers to the Weiner Diffusion model in which the drift is constant over time. Ornstein-Uhlenbeck types of model define the drift rate as decaying to an asymptote as the drift nears the threshold (Ratcliff & Smith, 2004). Accordingly, the drift rate is a representation of task complexity and choice discriminability (i.e. the ability to accurately order choice options). Also note that the variance of the drift rate results in choice being a probabilistic function of the model parameters and not a deterministic expression.

Decision Thresholds

In addition to the effect of drifts, the threshold parameter, θ, influences choice probability and deliberation time. The threshold may be conceived as a modulator for the speed-accuracy tradeoff. For a very high threshold, more samples of evidence need to be taken in order for accumulation to be sufficient to make a decision. Accordingly, the time taken to make a decision increases, yet this increase in decision criteria will increase the likelihood that the accumulation will cross the correct decision threshold. For a low threshold, fewer samples are required before a choice can be made, thus decisions will be quicker and made based on less evidence. Accordingly, a lower threshold will increase the likelihood that the choice will cross the wrong threshold. Hence, this threshold parameter is used to describe the effects of time-pressure whereby individuals must make quicker decisions based on less information (Dror, Busemeyer, & Basola, 1999), and an individual's desired level of confidence (Hausmann & Lage, 2008). Essentially, deliberation time (i.e. response time, RT) may be conceived of as follows (Busemeyer & Townsend, 1993):

$$Time = \frac{Distance}{Speed}\,, \qquad [2a]$$

$$Deliberation\;Time = \frac{Treshold}{Drift\;Rate}\,, \qquad [2b]$$

$$\mathrm{RT} = \frac{\theta}{\xi}. \qquad [2c]$$

Bias Parameter

The final important element of these models is that the decision does not need to always begin in an unbiased fashion. The initial preference state (i.e. the first impression), *z*, which in Figure 1 is equidistant between choice options, may begin closer to one threshold than the other (see Figure 2). Note that this parameter is referred to by a number of different names in different accumulative models such as; the *start point*, the *anchor point*, the *initial bias*, the *initial preference state*, or the *resting activation* (Albert, Aschenbrenner, & Schmalhofer, 1988; Aschenbrenner, Albert, & Schmalhofer, 1984; Busemeyer & Townsend, 1993; Diederich, 2003; Dror, Busemeyer, & Basola, 1999; Link & Heath, 1975; Nosofsky & Palmeri, 1997; Ratcliff, 1978; Ratcliff & Smith, 2004; Vickers, 1979; Wallsten & Barton, 1982). According to Busemeyer and Townsend (1993),

$$P(0) = \mathrm{z},$$

$$P(n) = P(n-1) + [\,V_A(n) - V_B(n)]$$

$$= z + \Sigma_k [V_A(k) - V_B(k)],\ k = 1, 2, ..., n. \qquad [2]$$

As a result of a bias towards choice *A*, the number of samples required to reach the *B* threshold increases and the probability of choosing *B* decreases, whereas, the number of samples required to reach the *A* threshold decreases, increasing the choice probability. As the number of samples required determines the response time, the model states that a bias like this has an effect on both decision likelihood and deliberation time. This parameter can be used to describe systematic preference reversals under time pressure (Busemeyer and Townsend, 1993). Appendix B outlines Busemeyer and Townsend's (1993) decision field theory model in more detail.

Relating Sequential Sample Models to the Four Characteristics

Returning to default-interventionism, the concept of a criterion threshold may be used to represent some of the aspects of the satisficing principle and the concepts associated with variation in individuals' thinking dispositions (type 3 processing). The satisficing principle states that individuals do not always employ all the resources at their disposal and may instead be "*settling for what is good enough*" (Evans, 2007a, *p*. 18), but the formal mechanism by which this assessment is made is still under debate (see Evans, 2007b; Evans, 2009). However, if we envisage decision-making as an on-going process of evidence accumulation, as described in the sequential sample models, we can envisage the threshold as a satisficing level. Until the threshold is met, the individual is unsatisfied and feels they need more evidence or to produce more hypotheses, i.e. the "*feeling of rightness*" (Thompson, 2009) has not been met. Once the threshold is met, the satisficing principle is met, and the individual feels capable of making their judgement.

In addition to delivering a potential way of accounting for type 3 processing, the sequential sample model framework is also useful because it enables us to differentiate between early versus late information by formally identifying preferences state by order of consideration over time. The preference state at the current time is the *n*th sample $P(n)$, the accumulation up to the present time is the accumulation $P(n - 1)$, and future preference states are $P(n + 1,2,3,...,i,$ etc.). This enables us to identify a piece of evidence being gathered during a decision via its serial position index.

Furthermore, we can differentiate between the default, type 1 response, and subsequent slow and effortful type 2 responses. Recently, it has been suggested that an effective means of differentiating between type 1 and type 2 processing is via the role of working memory by each (Evans, 2009). Type 2 processing appears to rely heavily on working memory and these results in a slow, serial, processing of information which occurs over a period of time. Type 1 processing on the other hand, does not appear to rely on working memory and so can provide rapid responses with little awareness of cognitive effort. Assuming that the rapid, automatic, type 1, response to a choice problem provides the initial valence value, this default response can be assigned to the first preference state between options A and B at time zero. This type 1 response is assigned the special parameter, z.

$$\text{Default (Type 1) response} = P(0) = z = [V_A(z) - V_B(z)], \quad [1a]$$

Type 3 processing of this type 1 response may determine that the preference state is not yet convincing enough to make a decision and intervention from type 2 processing is required. This assessment can be described using the satisficing decision threshold, θ, parameter which must be passed by the preference state before a decision can be made. Thus, if the type 1 response is satisficing enough $|P(0)|, |z| \geq \theta$, then a choice is made based on the valence of the preference state entirely driven by type 1 responses. If the type 1 response is not satisficing enough, $|P(0)|, |z| < \theta$, then more evidence must be gathered to make the choice whereupon type 2 processing intervention is triggered resulting in greater involvement of working memory. In order to capture the slow, sequential, working memory intensiveness of type 2 processing, valence values are generated over time which accumulate as preferences states as follows:

$$\text{Default (Type 1) state, } P(0) = z \quad [1a]$$

$$\text{First Type 2 state, } P(1) = P(0) + [V_A(1) - V_B(1)], \quad [1b]$$

$$\text{Second Type 2 state, } P(2) = P(1) + [V_A(2) - V_B(2)], \quad [1b]$$

$$\text{Third Type 2 state, } P(3) = P(2) + [V_A(3) - V_B(3)], \text{ etc.} \quad [1b]$$

$$n\text{th preference state, } P(n) = P(n\text{-}1) + [V_A(n) - V_B(n)], \quad [1c]$$

The more type 2 samples, the more likely that the drift will pass the correct threshold (assuming type 2 processes are capable of detecting the correct choice given enough time) and the less the type 1 response will predict the decision outcome. The fewer the type 2 samples, the greater the impact of the type 1 response. I define this intervention mechanism, therefore, as an *outweighing* mechanism in which the default type 1 response is not ignored or taken “offline” but simply has a reduced overall weight as more type 2 processing is allowed by the threshold. The higher the satisficing threshold, the more type 2 processing contributes to the overall preference state and therefore the less type 1 processes contribute.

Given that the number of samples taken may vary depending on the decision threshold, a sequential sample model can be used to predict the total evidence required by an individual. This is expected to correlate with the individual's satisficing criterion level. For example, with a low satisficing threshold the individual may be satisfied by the early information, i.e. the initial preference states they form. Therefore, such an individual might be expected to gather only a small amount of information. Whereas, if an individual has a high threshold then they may not be satisfied by the early information and may therefore gather more evidence in order reach this higher threshold. Thus, it is possible to predict how type 3 processing should impact on the total evidence volume required by the individual. As time increases with the number of samples accumulated (due to working memory limitations), a potential correlate with this type 3 processing may be the deliberation times (or RTs). The sequential sample model approach may therefore enable us to predict RTs and how RTs might be affected by certain factors relating to satisficing thresholds and initial dispositions.

Of course, it should be apparent that dual-process theory as a whole is far more nuanced in regards to the relationship between type 1 and type 2 processing. Indeed, reducing type 2 processing to being represented simply by drift rates does not fully represent dual-process theory literature. However, the intention of building this model is not to attempt to capture all aspects of dual-process theory or default-interventionism. Rather the aim is to initially construct a simplified quantitative model inspired by dual-process concepts and then test the extent to which this basic quantitative model may improve our understanding of the roles of early-informational biases in JDM. Following the law of parsimony, I believe it is more beneficial to demonstrate the value of a simplistic model and then consider adding and evaluating further complexity in subsequent development stages only if required. In order to demonstrate how a simplified version of default-interventionist concepts can be of benefit to our understanding of both early versus late information in JDM, I now present the results of some simulations using this model.

A Sequential Sample Model Simulation of Default-Interventionism

In order to demonstrate how a quantitative model of default-interventionism can provide predictions of the impact of early information on decision-making in different circumstances, I now present the results of some sequential sample model simulations. The simulations were run in R (http://www.r-project.org/) and the code is shown in Appendix C. The model simulates 100 individuals choosing between choice A or choice B. Choice A is the better of the two choices and therefore is assigned a positive drift rate ($\xi > 0$). This assumes that, on average, individuals will tend to observe that choice A is favourable but that errors in this assessment will occur and these random variations are captured by the variance in the drift rate. This is accounted for by setting a high standard deviation ($\sigma = 4$), i.e. the degree of volatility in preference state based on the same evidence. For the default type 1 response, the initial start point parameter z is assigned a value; $z = 0$, 10, or -10. If the z value is positive ($z > 0$) then the individual's type 1 response favours choice A, i.e. it is *congruent* with the normatively optimal choice (Choice A). If the z value is negative ($z < 0$) then the individual's type 1 response is *incongruent*, favouring the worst choice B. When $z = 0$ the type 1 response is uninformative and the individual has no intuitive response regarding the alternatives. Subsequent to the type 1 response are the type 2 processes which accumulate over time as evidence is gathered, interpreted, and evaluated. As these responses are accumulated, each preference state is iteratively evaluated by the type 3 processing in order to determine whether a choice can be made, that is, whether or not the satisficing principle is deemed to have been met. In the model, this type 3 assessment is based on the threshold parameter, θ, as a criterion. A high threshold, e.g. $\theta = 20$ in this simulation, indicates that the individual has a strong need or motivation for cognition, and a low threshold, e.g. $\theta = 5$, indicates a low need for cognition either due to a lack of motivation or some external pressure such as time pressure.

Simulation Results

The results of the first simulation in Figure 2 show a case in which the threshold is high ($\theta = 20$) and there is no bias from the type 1 response. The simulation shows that 93% of the participants correctly chose the correct alternative (A) but some made mistakes due to the difficulty of the task, represented by the drift rate and standard deviation parameters. The median deliberation time for choice A is shown by the blue vertical bar and the median deliberation time for choice B is shown by the red vertical bar. Those that finally chose A are shown as blue lines and those that finally chose B are shown as red lines.

Figure 3 shows the results of the second simulation which replicates simulation 1 but with a stronger drift rate ($\xi = 2$). This would represent a situation in which the information examined is more strongly indicative of choice A. This may be a result of a change in task itself but also may represent a shift in sampling behaviour. For example, it may be the case that, for some reason, individuals tend to bias their investigation of choice information in ways which tend to favour one choice over another. This would result in a bias towards choosing A because the information examined is biased in favour of A and this is demonstrated by the increase in the probability of choosing A over B (from 93% in simulation 1 to 98% in simulation 2). However, the sequential sample model indicates that this would not only impact on choice probabilities but also decrease deliberation times (i.e. the speed at which the satisfying criterion is met) because preference states can reach the threshold more rapidly. Thus, A in Figure 3 is chosen more readily based on less information when compared to A in Figure2.

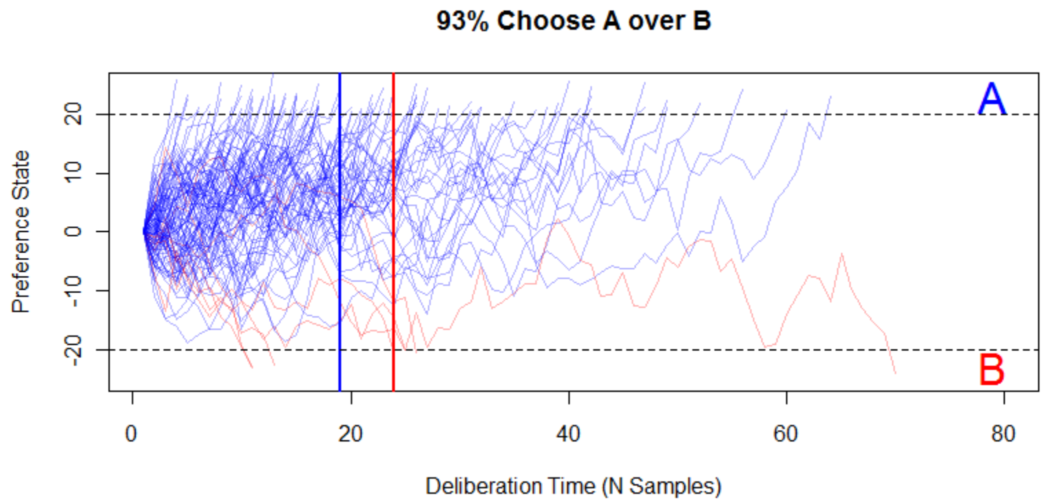

Figure 2. Simulation 1: ξ=1, σ=4, z=0, θ=20. The blue bar indicates the median deliberation time for those that chose A, and the red bar indicates the median deliberation time for those that chose B. A choosers are shown in blue; B choosers are shown in red.

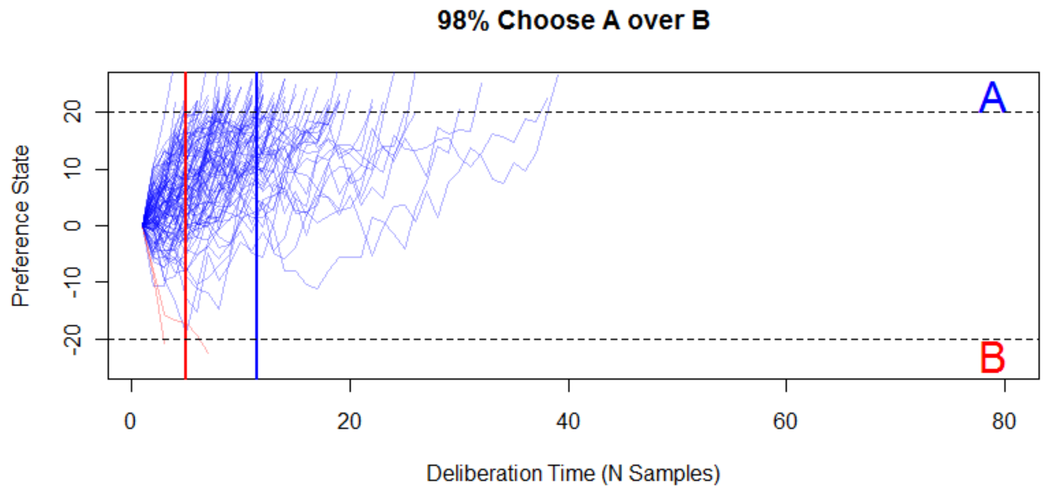

Figure 3. Simulation 2: ξ=2, σ=4, z=0, θ=20. The blue bar indicates the median deliberation time for those that chose A, and the red bar indicates the median deliberation time for those that chose B. A choosers are shown in blue; B choosers are shown in red.

Figure 4 shows the results of a simulation in which the satisficing threshold is drastically reduced. In this simulation, choices are made very quickly (both vertical bars are low compared to the simulation in Figure 1) and this increase in speed comes at a price of accuracy. Now, only 69% chose the correct alternative. Due to the low threshold, individuals may happen to consider good aspects of B and thus pass the wrong threshold before they have carefully considered the good aspects of A. Due to the fact that the type 1 response is uninformative (z=0), they cannot use their intuitive thinking to help them deal with this low threshold. This is a traditional speed-accuracy tradeoff.

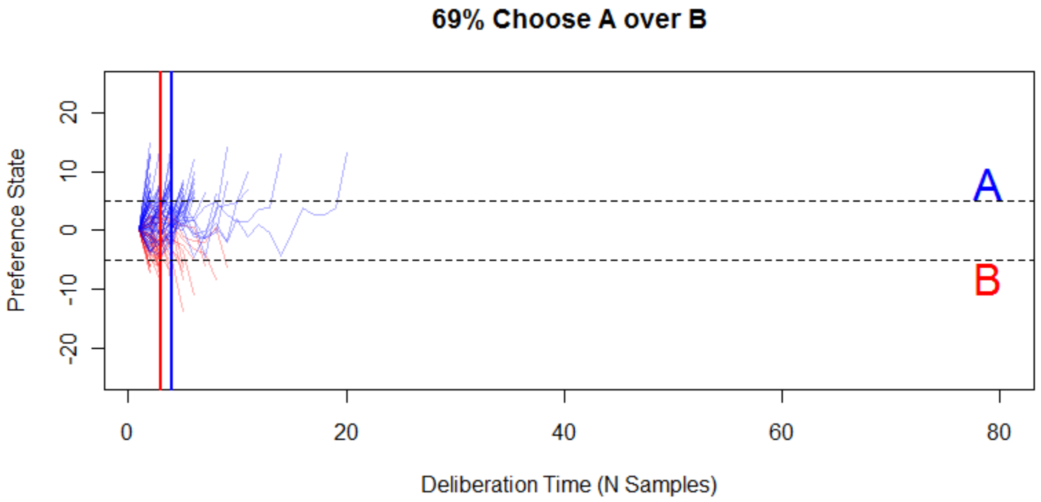

Figure 4. Simulation 3: ξ=1, σ=4, z=0, θ=5. The blue bar indicates the median deliberation time for those that chose A, and the red bar indicates the median deliberation time for those that chose B. A choosers are shown in blue; B choosers are shown in red.

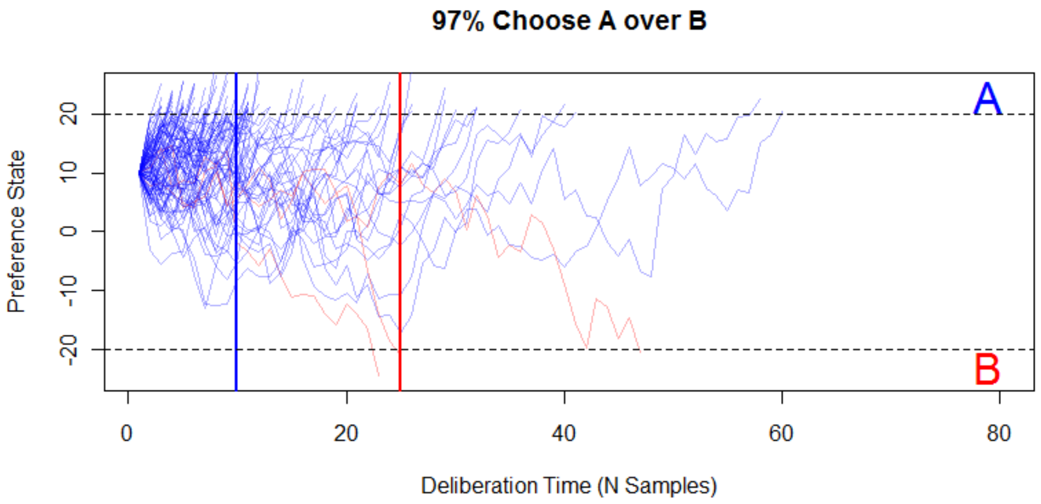

Figure 5. Simulation 4: ξ=1, σ=4, z=10, θ=20. The blue bar indicates the median deliberation time for those that chose A, and the red bar indicates the median deliberation time for those that chose B. A choosers are shown in blue; B choosers are shown in red.

The results in Figure 5 show the effect of a strong type 1 response that is in favour of the normatively correct choice, i.e. their intuition is correct. This is represented by a z-parameter which is biased towards choice A (z = 10). Essentially, the type 1 response means that they have partially made their mind up already but, due to the high threshold, they hold off making a choice until they have confirmed/disconfirmed this belief. Nevertheless, the results show that very few individuals choose B because they have two sources of information driving them towards the correct choice – the type 1 initial bias towards A and the drift towards A from type 2 thinking. Therefore, the simulation models a *congruency* effect of type 1 and type 2 responses. Furthermore, not only do more individuals make the correct choice but they do so faster than they did in simulation 1, reducing their deliberation time from 19 samples down to 10, as shown by the vertical blue bar. Thus, congruency is also related to the rate at which the satisficing criterion is met.

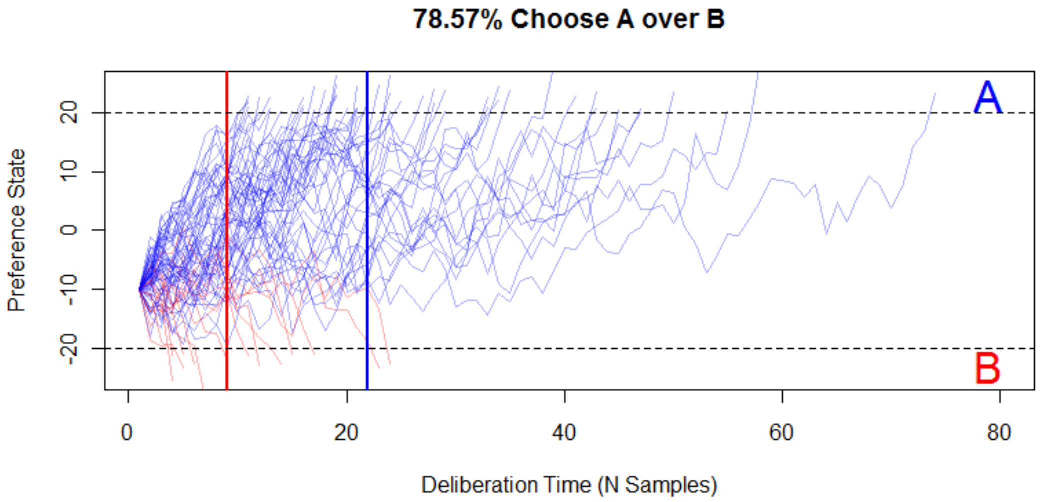

Figure 6. Simulation 5: ξ=1, σ=4, z=10, θ=20. The blue bar indicates the median deliberation time for those that chose A, and the red bar indicates the median deliberation time for those that chose B. A choosers are shown in blue; B choosers are shown in red.

The results of the fifth simulation (Figure 6) show an *incongruency effect*, i.e. the effect of different type 1 and type 2 responses. This impacts on the performance resulting in more errors as individuals are biased by an erroneous first impression. Again, the effects are not only observed in the choices but also in the deliberation times. Now, the bias towards the B threshold means that the individual only needs a small amount of evidence in favour of B to sway them, whereas in order to choose A they need much more evidence. This impacts on deliberation times as well whereby errors towards B are due to the small distance between the type 1 response towards B and the B threshold, whereas A choices take longer (blue vertical bar is beyond the red vertical bar) due to the preference accumulation having to outweigh the initial bias towards B (an incongruency effect).

Discussion of Simulation Results

These simulations demonstrate how it might be possible to represent some of the aspects of default-interventionism for JDM through a quantitative model and how early (more type 1 oriented) and late (more type 2 oriented) information may be modulated via a satisfying threshold (type 3 processing). The results demonstrate four potential areas of interest which are suitable for empirical study.

(1) Evidence of type 3 processing: the satisficing principle

The first benefit of such a model is that we can make predictions regarding the recently proposed type 3 processing for JDM tasks (Evans, 2009; Stanovich, 2011). In particular, the sequential sample approach can model evidence volumes and response times and these are proposed to be correlated with type 3 processing and the satisficing principle. In JDM, these have tended to be neglected in favour of measures which relate to the algorithmic, type 2, processes; for example, biases in information types sought, preference reversal, etc. The first application of the sequential sample model, therefore, is that it can be used to predict when and how we might observe *evidence of type 3 processing*. For example, simulation 2 shows how a higher drift rate should result in quicker decisions based on less samples of evidence. Therefore, any behaviour which results in an increase in drift rate, i.e. an increase in the change in preference state per sample of evidence, should impact on the time taken to meet the satisficing threshold. If an individual was to consider evidence in a biased manner, i.e. ways which promote one outcome over another, the average perceived benefit of that alternative compared to the other may be exaggerated. Therefore, the average increase in preference state per sample (drift rate) towards the biased alternative should be higher. Based on this, the model can predict that in a JDM task in which sampling is biased towards a certain outcome, the drift rate will be higher, and therefore the satisficing principle will be met based on fewer items of information. As the number of samples is related to the overall deliberation time, response times should therefore also shorten compared to a scenario in which evidence gathering is fair and balanced.

This clearly has direct application to studies of biased predecision processes (Brounstein, 2003) and selective sampling of information described in Chapter I. While these studies have explored the types of evidence gathered when biased precision processing occurs, I am unaware of any that have also focused on the volume of information required when biased predecision processing occurs. This not only has the potential to develop our understanding of the nature of biased predecision processing by examining the implications of type 3 processing in a study of biased predecision processing. This issue is explored in Chapter IV.

(2) Congruency of type 1/type 2 processing in JDM: the congruency effect

Stanovich's (2011) model of dual-process mediation is based on overriding type 1 responses through an individual's need for cognition or reflectiveness. However, it is unclear as to exactly how this overriding takes place. It might be that a type 1 response is simply *"taken offline"*, i.e. it is actively suppressed or ignored in the deliberation process. However, the sequential sample model outlined above captures a different method for default-interventionism which is a process of *outweighing* rather than active suppression. Under the sequential sample mechanism the early type 1 responses (z parameter) still input into the judgement when type 2 processing is engaged, but the overall impact of the type 1 processing in the final judgement reduces as more type 2 processing is employed. If a threshold is reached after only a few type 2 processing samples, the initial type 1 response may have a greater overall weight than if the threshold requires dozens of samples from type 2 processing. Such a proposal can be tested. For example, as shown in simulations 3 and 4, a sequential sample framework makes predictions regarding the effect that congruency of type 1 and type 2 processing has on evidence volumes and hence RTs (i.e. related to type 3 processing). The geometry of the sequential sample model means that the number of samples required to correct an incongruent type 1 response should be more than the numbers of samples required to reinforce a congruent type 1 response. This is the congruency effect. If it was the case that type 1 processing is ignored in type 2 intervention scenarios, such a congruency effect would not occur as the z-bias would be removed rather than outweighed.

The simulations of the congruency of the z and ξ parameters predict similar results to those found by Evans, Barston, and Pollard (1983) in their study of belief bias. In their experiment they gave participants statements and conclusions which were either believable or unbelievable from experience, and either valid or invalid by formal logic. Under the assumption that believability is related to type 1 processes and logical validity is more related to type 2 processes, their study revealed that more correct decisions are made when both responses agree than when they do not (see Table 2). This was the case despite participants being asked to use strict deductive reasoning, a motivation to use just type 2 processes. The results of the simulations echo these findings. The question remains, therefore, as to the extent to which the sequential sample model prediction of congruency in JDM reflects empirical behavioural data. The congruency effect is examined in both chapter V and chapter VI.

Table 1. Evidence of belief Bias in Syllogisms from the work of Evans, Barston, and Pollard (1983) with percentage of correct conclusions. The table shows positive signs for type 1/type 2 responses that indicate validity and negative values to responses indicating invalidity.

Example	Congruency	Accuracy	Correct Response
Valid/Believable = Type 2 + Type 1	Congruent	89%	Valid (+)
Valid/Unbelievable = Type 2 – Type 1	Incongruent	56%	Valid (+)
Invalid/Believable = (– Type 2) + Type 1	Incongruent	29%	Invalid (−)
Invalid/Unbelievable = (– Type 2) – Type 1	Congruent	90%	Invalid (−)

(3) Continuous rather that diametric/categorical predictions of dual-process effects: continuous predictions

The third aspect relating to this sequential sample approach is that the model can make predictions over a range of values. Many JDM studies are restricted to categorical or diametric predictions. For example, the studies of time pressure are usually restricted to “present” and “absent” time pressure conditions. In such studies it is observed that the individuals make their decisions using different information in the pressured and unpressured conditions. For example, under time pressure conditions, compared to no time pressure conditions there is a greater use of emotional thinking and affect heuristics (Finucane, Alhakami, Slovic & Johnson, 2000), and the consideration of moods (Noda, Takai, & Yoshida, 2007) as well as primacy effects in impression formation, the tendency to use ethnic stereotyping, and anchoring in probability judgements (Freund et. al, 1985; Kruglanski & Freund, 1983). These findings do fit the “toolbox” account of adaptive decision behaviour as there are clearly differences in kinds of information used in the different conditions. However, as discussed, the same behaviour could equally, and in my view more parsimoniously, be explained via a default-interventionist approach and a criterion-oriented mediation (i.e. satisficing principle).

The sequential sample model uses a satisficing threshold parameter, i.e. criterion-oriented strategy, selection based on the ideas of default-interventionism. Thus, rather than selecting a more heuristic versus normative oriented strategy based on an expectation of time pressure (i.e. the adaptive decision-maker hypothesis), default interventionism simply occurs which automatically selects a reasonably optimized strategy for the level of time pressure. I refer to this default-interventionist modulation as *optimized* rather than *optimal* as currently I am unaware of any study which evaluates the effectiveness of a default-interventionist approach against adaptive decision strategies. Nevertheless, the ability to adapt cognitive effort within a decision without *a priori* strategy selection would appear to be a more effective means of adapting behaviour to constraints, especially in novel or unexpectedly constrained situations (see Chapter VII). When there is high time pressure the threshold is low and so type 2 processing does not get much of a chance to outweigh the rapid default response. Whereas, under no time pressure a higher satisficing threshold allows a great deal of type 2 processing which either outweighs an incongruent type 1 response or confirms a congruent type 1 response. Critically, any degree of time pressure between these two ends of the spectrum is catered for simply by raising or lowering the satisficing threshold (i.e. via type 3 processing).

The continuous predictions made by this model could be combined with the congruency effect predictions to determine whether the predicted relationship between congruency/incongruency of type 1 and type 2 processing over a range of time pressures matches the behaviour observed in the empirical data. This issue is tested in Chapter V.

(4) A proposed mechanism for type 1 bias in two-choice decision-making: sequential sample versus alternative race model – an incongruency effect

The sequential sample model above may be envisaged as a "*tug-of-war*" game between two alternatives. The type 1 processing defines whether the game begins with both alternatives equidistant from their respective thresholds or closer to one threshold than the other (i.e. an unfair tug-of-war game). As shown in Figure 5, the sequential sample model represents a type 1 response towards one alternative as a shift in the start point towards the threshold for that alternative. Most importantly, the structure of the mechanism also involves a movement *away* from the threshold for the other alternative (see Figure 5). Thus, in addition to the role of congruency of type 1 and type 2 processing in reducing deliberation times and increasing decision accuracy (if type 1 and type 2 processing favour the normatively correct choice), there is also a hypothesised *incongruency effect.* Whereby, if type 1 processing goes against the type 2 processing information, then the sequential sample model predicts increased deliberation times and potentially reduced accuracy (depending on the level of the satisficing threshold and assuming that type 2, but not type 1, processing favours the normatively correct decision). This is a result of the sequential sample mechanism, but is not the only way that type 1 biases may be modelled.

An alternative version would be to consider a *race model* (Ratcliff & Smith, 2004) in which a bias from type 1 processing in favour of one alternative (B in Figure 6) does not negatively impact on the distance that the other (A in Figure 6) alternative must travel (see Figure 6 as an example of an unfair race model). Rather the two threshold distances are independent such that a bias towards one does not impact on the distance to the other. Again, the winner is simply the first accumulation to pass the final threshold.

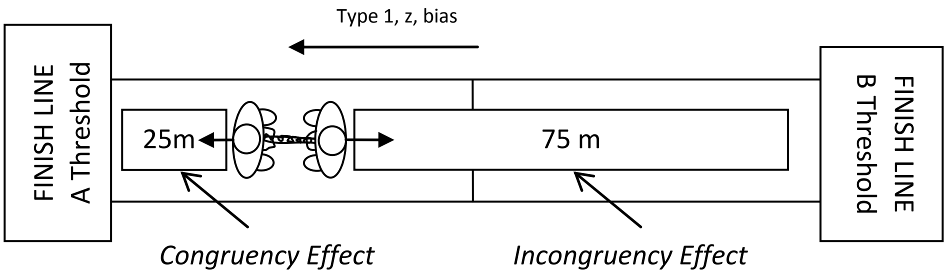

Figure 5. A "Tug of War" depiction of the sequential sample model proposed in this chapter and the effect of a bias from type 1 on the distance to each threshold. A bias towards one threshold (A) negatively impacts on the distance to the opposing threshold (B).

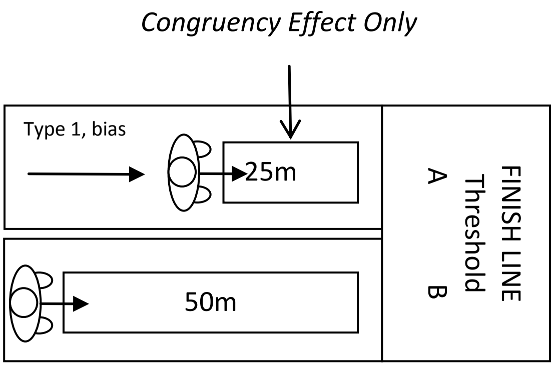

Figure 6. An alternative, race model, depiction of type 1 bias showing the effect of a bias from type 1 processing on the distance that must be travelled by each choice. A bias towards one threshold (A) does not negatively impact on the distance to the other threshold (B).

The sequential sample model I outlined in this chapter is based on the tug of war, rather than the race model mechanism. Therefore, it would be interesting to test which of these approaches is a better representation of type 1 bias in two choice tasks. This should be very simple to test. If it is found that a bias towards one conclusion influences the time taken to form the opposite conclusions then there is strong evidence that a sequential sample, rather than a race model mechanism, is more likely. This is because the RTs for the incongruent hypothesis would only be affected if a tug of war, rather than race, mechanism is being used. This question is addressed in Chapter VI.

Conclusion

The sequential sample approach outlined in this chapter is a basic quantitative model for representing deliberation over time, and therefore provides a framework for understanding the bias of early information and the role of type 3 processing in mediating these biasing effects. In particular, the sequential sample approach allows for the investigation of four predicted characteristics inspired by dual-process concepts.

Chapter IV will focus on the first question: acquiring evidence of type 3 processing. Based on the sequential sample model, I predict that measuring the volume of information gathered and response times may provide a valuable insight into this type 3 processing and the point at which a decision-maker attains a "feeling of rightness" or meets their satisficing threshold. As discussed in this chapter, studies investigating biased predecision processing focus on biases in the types of information gathered but do not consider dual-process explanations and especially the recently proposed type 3 processing. However, the sequential sample model simulations (comparison of simulations 1 and 2) make predictions regarding how this selective evidence gathering might impact on the total evidence gathered and also the correlated measure of deliberation times (RT).

Chapter V seeks to explore the second and third aspect relating to the sequential sample model. In particular, I seek to explore the interaction between time pressure (simulation 2) and the congruency effect (simulations 4 and 5). However, more than simply exploring categorical predictions, I aim to examine whether the characteristics of empirical choice data match the characteristics of the sequential sample model over a range of time pressures. The evaluation of the sequential sample model will be based on whether or not the changes in choices, as a result of changes in time pressure, are similar to the predicted changes based on the sequential sample model. This chapter, therefore, involves descriptive evaluation of the sequential sample model.

Chapter VI will focus on the congruency effect as well, but this time in a competitive models situation. The aim is to determine whether the sequential sample model's tug of war mechanism is a better description of the effect of early informational biases than a race model mechanism. Both mechanisms make different predictions regarding how early information in favour of one hypothesis should impact on distance to the alternative hypothesis threshold. Therefore, it is possible to test these predictions against empirical data. In contrast to Chapter V, which is simply a descriptive evaluation of the sequential sample model, this chapter involves competitive evaluation of the sequential sample model.

The evaluation of the simulation predictions of JDM behaviour will form the central aim of this thesis from this point onwards. As the sequential sample model is based on the four aspects outlined in Table 1, successes using this model have implications for dual-process theory, and default-interventionism in particular. Weaknesses, however, may be attributable to two causes: (1) limitations of default-interventionism in the JDM domain, or

(2) limitations in the sequential sample model to adequately represent default-interventionism. I will conclude by assessing both the application of dual-process theory to the various JDM domains studied in this thesis, as well as assessing the strengths/limitations of the sequential sample model and how it may be improved.

Summary Points

- The recent proposals in the dual-process literature regarding type 3 processing (reflective mind reasoning) seems highly relevant to the aim of understanding when early (type 1 processing) informational biases might/might not occur.
- The emphasis in the JDM domain on choosing between "strategies" neglects the role of implicit type 1 processing and leads to unresolved questions relating to the mechanism by which these strategies are effectively and efficiently selected.
- I introduce a basic dynamic modelling approach for accounting for default early type 1 biases, the intervention of the working-memory intensive, type 2, processing and type 3 processing mediation of this intervention via a satisficing threshold (a criterion-, rather than strategy-oriented, adaptive decision mechanism).
- The aim of the thesis is now to assess the strengths and limitations of this sequential sample model approach for representing the role of dual-process concepts in understanding the early-informational biases in JDM.

Chapter IV – Empirical Chapter

"Prejudice is a great time saver. You can form opinions without having to get the facts."

- E. B. White (American writer, 1899-1985)

As discussed in Chapter I, there are many sources of what I describe as early-information biases. One such source may be an initial disposition towards the item being judged. On approaching information concerning an item, an individual may have a degree of background knowledge or previous encounters with the item. For example, an interviewer may have read a candidate's curriculum vitae prior to interviewing them or a consumer may have heard someone's opinion regarding a car prior to taking a test drive. Studies into the effect of this early information often results in biases in evidence gathering strategies. In particular, theories of cognitive coherence (Holyoak & Simon, 1999; Simon, Krawczyk, & Holyoak, 2004; Simon, Snow, & Read, 2004) and biased predecision processing (Brownstein, 2003) relate to these biases and will be the focus of this chapter. These theories attempt to explain why it is that individuals tend to employ biased evidence gathering strategies which tend to result in reinforcement, rather than challenge, of the initial disposition. Based on this research the following empirical chapter will explore the role of early information in evidence gathering strategies and which types of information individuals tend to select depending on their initial dispositions.

As discussed in Chapter III, dependent measures which focus on the types of information used to form a judgement capture elements of type 1 and type 2 processing. However, the sequential sample model simulations in Chapter III also discussed the notion of measures of behaviour which may relate to a third type of processing regarding the "feeling of rightness" or the satisficing principle (type 3 processing). I hypothesised that we may be able to gain evidence of the effect of this third type of processing by exploring the total volume of evidence gathered depending on the early information. As interventionist type 2 processing is said to be slow and effortful, I also discussed the potentially correlated indicator of type 3 processing effects, deliberation time (RT). Explanations of biased predecision processing (see Chapter I) have tended to ignore dual-process theory in their accounts. Therefore, the following empirical chapter will examine whether dual-process concepts are useful in this domain of research. In particular, this chapter shall test the sequential sample model predictions regarding the effects of early information on evidence volumes and deliberation times (i.e. evidence of type 3 processing).

Bounded Evidence Gathering: Biased predecision Processing in evaluation of a novel single item[5]

Abstract

This study investigates the amount and valence of information selected during single item evaluation. One hundred and thirty-five participants evaluated a mobile phone by reading hypothetical customers' reports. Some participants were first asked to provide a preliminary rating based on a picture of the phone and some technical specifications. The participants who were given the customer reports only after they made a preliminary rating exhibited valence bias in their selection. In contrast, the participants who did not provide an initial rating sought subsequent information in a more balanced, albeit still selective, manner. The preliminary raters used the least amount of information in their final decision, resulting in faster decision times. This finding is in support of the hypotheses relating to type 3 processing based on the sequential sample model simulations presented in Chapter III. The results appear to support a dual-process account of selective exposure to information and the development of subjectively coherent mental models. Such dual-process explanations have tended to be neglected in biased predecision processing accounts.

Introduction

In order to make accurate judgements it is critical that decision-makers limit any biased processing of evidence prior to the final choice which may be detrimental to a fair assessment of all the information available. Yet, evidence suggests that biased processing of information frequently occurs during judgement and decision-making (Brownstein, 2003). A number of studies have demonstrated that people use both selective exposure to information (e.g., Schulz-Hardt, Frey, Luthgens, & Moscovici, 2000), and selective processing (e.g., Russo, Medvec, & Meloy, 1996), biasing their decision-making. Virtually all current theory of biased predecision processing (see Mills & O'Neal, 1971; Kuhl, 1984; Beckmann & Kuhl, 1984; Montgomery, 1983, 1989; Svenson, 1992, 1996, 1999; see Brownstein, 2003, for review) involve the identification of an *early favourite* prior to the final judgement. In multi-alternative decisions, this early favourite may be an alternative which initially looks promising. Individuals are then said to employ biased processing of the alternative attributes by bolstering their evaluation of the favourite's attributes in comparison to the other alternatives. Furthermore, subsequent information searching is often biased, which helps to support the view that this early favourite is indeed the best alternative. This study will focus

[5] Published Article: Fraser-Mackenzie, P.A.F. & Dror, I.E. (2009). Selective information sampling: Cognitive coherence in evaluation of a novel item. *Judgement and Decision Making, 4(4)*, 307–316

on this second phenomenon; "*selective exposure*" to information during evidence gathering. Selective Exposure means that people select evidence in a fashion which neglects certain valences of information in favour of others resulting in an imbalance in information gathering. For example, an individual restricting their exposure only to positive aspects of a potential course of action may result in neglect of negative aspects potentially distorting their impressions.

Selective exposure to information

Explanations of selective exposure to information are frequently discussed in terms of cognitive dissonance theory (Festinger, 1957, 1964) and *motivational* processes. The theory proposed that, having made a choice, negative affect is experienced as a result of the negative aspects of the choice and the positive aspects of alternatives. Thus selective exposure to information is driven by a form of motivated reasoning (Kunda, 1990) in order to avoid negative affect. Although cognitive dissonance theory was initially assumed to be a post-decisional process, more recent theorists argue that that selective exposure can occur before making a final choice (see Brounstein, 2003, for review). According to Brounstein (2003), biases in processing prior to making a choice may derive from the competition between the competing alternatives and hence the need to differentiate between the early favourite and the competing alternatives. Essentially, the biases are hypothesised to derive from some form of motivated reasoning (Kunda, 1990), whereby individuals engage in a degree of selectivity of exposure or biased evaluation of information to support one choice over others.

However, many everyday tasks involve evaluating single items with no alternatives. For example, we may be deciding whether or not to buy an auction item, we may be evaluating a piece of evidence as a member of a jury, we may be judging a speech made by a member of parliament, or attempting to evaluate a person's character. Whilst motivational theories can account for pre-decision biases prior to choice between competing options or where some personal stake in the outcome is expected, it is more difficult to understand how motivational processes could account for hypothesis testing in the evaluation of a novel single item. Instead, Bond, Carlson, Meloy, Russo, and Tanner (2007) cite a cognitive, rather than motivational, explanation based on the concept of *cognitive coherence* (Holyoak & Simon, 1999; Simon, Krawczyk, & Holyoak, 2004; Simon, Snow, & Read, 2004). The essence of the theory is that the mind tends to dislike incoherent information and is designed to naturally form connections between pieces of information in order to build a subjectively coherent, although potentially inaccurate, mental model. The mind is said to "*shun cognitively complex and difficult decision tasks by reconstructing them into easy ones,* *yielding strong, confident conclusions*" (Simon, 2004). The cognitive coherence hypothesis, therefore, predicts pre-commitment biases in the evaluation of attributes prior to judging a single novel item. Surprisingly, despite the new focus towards cognitive psychological accounts, dual-process theories have been neglected in this field.

Dual-Processes

As discussed, biased predecision processes appear to involve the identification of an early favourite alternative (in multi-alternative decisions) or hypothesis (in single item evaluation). This is also predicted by one of the fundamental principles of Evan's (2007a) theory of hypothetical thinking: the *singularity principle*. This principle argues that, due to the limits of working memory, we tend to consider one hypothesis at a time. The *relevance principle* (Evans, 2007a) proposes that individuals will initially consider the most subjectively relevant cues (initially triggered on type 1 processing) based on task features, the current goal, and background knowledge. So suppose one is attempting to decide how we rate a potential new product (e.g. a mobile phone). Our initial mental model of our personal rating of the phone is likely to be formed based on our past experiences, or perhaps the way the phone is presented to us, or whether the phone appears to meet our current needs. This first hypothesis must be assessed against the third of Evans's (2007a) principles: the *satisficing principle*, i.e. an assessment of this initial hypothesis regarding whether more evidence gathering is required (type 3 processing)? If more evidence is required (i.e. the satisfying threshold is not met) then the individual may engage in type 2 processing to gather more information. Due to the singularity principle, however, this type 2 processing will tend to naturally focus on the information which relates to the current hypothesis (i.e. the type 1 produced hypothesis) due to the relevance principle. This searching continues until either the individual feels satisfied with the judgement of the phone or they find some contrary evidence which forces them to change their mental model.

This cognitive process, which is based on the singularity, relevance, and satisficing principles, appears to reflect the kinds of biases observed in studies of biased predecision processing: (1) the identification of an early favourite (i.e. the initial type 1 triggered hypothesis); (2) that subsequent evidence gathering is focused around this hypothesis; (3) often resulting in the neglect of alternative options and imbalances in evidence gathering (see, Mills & O'Neal, 1971; Kuhl, 1984; Beckmann & Kuhl, 1984; Montgomery, 1983, 1989; Svenson, 1992, 1996, 1999).

Sequential Processing and Selective Exposure

The theory of cognitive coherence also has similarities to dual-process theory, in particular, regarding the nature of the hypothesised type 3 processing discussed in Chapter

III. In Chapter III, I described deliberation as a sequential process of collection and evaluation of information. The argument here is that during the evaluation of a single novel item, evidence is selected with the aim of increasing the cognitive coherence of the current mental model until the satisficing threshold is met. Evidence in support of this view is demonstrated by Jonas et al. (2001) who explored selective exposure to information with an accumulative paradigm comparing a sequential search task against a simultaneous search task. A sequential search task allows participants to read each selected item of information before they move on to the next. A simultaneous search task forces participants to select all the information they think they would like to read before they see any of the results of their selections. Jonas et al. found that when the information was presented sequentially, the selectivity of exposure was greater than when the information was presented simultaneously.

The fact that selective exposure effects are facilitated by a sequential task suggests that information selectivity is not simply based upon carrying out an *a priori*, predefined search strategy, but instead represents an ongoing and accumulative process of evidence gathering, type 3 assessments, and feedback (see Chapter III and Chapter VI for further discussion of *a priori* strategy selection versus criterion-oriented adaptive decision mechanisms). When individuals gather evidence, they develop their mental representation of the novel item through this information and further evidence gathering is selected based on an expectation of which information types the searcher believes may most effectively develop this mental representation. This iterative process of evidence accumulation and hypothesis evaluation fits nicely with the heuristic-analytic theory shown in Figure 1 Chapter I. Interestingly, the descriptions of theories of biased predecision processing have some strong similarities to the sequential sample model approach outlined in Chapter III and some degree of type 3 assessment. The theories suggest: maximising choice certainty (Mills & O'Neal, 1971), bolstering intention until ready to act (Kuhl, 1984; Beckmann & Kuhl, 1984), restructuring the decision environment until full dominance occurs (Montgomery, 1983, 1989), or differentiating until a sufficiently superior alternative emerges (Svenson, 1992, 1996, 1999). Essentially, all these theories imply that the decision-maker must reach a critical point of coherent differentiation between elements at which point the judgement can be made. I hypothesise that this point may depend upon the perceived cognitive coherence of the current hypothesis reaching the satisficing threshold, i.e. the individual feels that their mental representation of the differences between alternatives is coherent to a level which meets their satisficing criteria.

Sequential Processing and the Satisficing Principle: Type 3 Processing

Based on the dual-process account described above, I predict that a weak initial hypothesis, based on limited background knowledge or uninformative early information, may result in more variation in evidence gathering. This is because there is little background information for the type 1 processing to provide a firm initial starting point. Therefore, individual may change their initial hypothesis more frequently as they explore, and engage with, the various sources of information. In comparison, an individual with a stronger initial hypothesis, based on past experiences or salient initial information (type 1 processing), would be predicted to be less varied in their evidence gathering focusing. In agreement with both the dual-process, and biased predecision processing literature, these individuals may focus more towards information that relates to that initial hypothesis.

Based on simulation 2 (cf. simulation 1) in Chapter III, I would expect this selective exposure to information to result in a more rapidly evolving mental model, i.e. cognitive coherence should reach the satisficing threshold at a faster rate. Therefore, the point at which this hypothesis is deemed to be strong enough to pass the satisficing threshold should occur sooner under selective exposure than under a more varied search pattern. This means that those individuals that display strongly selective exposure should make their judgements based on fewer items of information and possibly also make their judgements in less time. This prediction regarding type 3 processing, based on the simulations in Chapter III, is tested in this empirical study.

Experiment

The task chosen was rating a hypothetical mobile telephone as one might in an online shop like Amazon.com, i.e. rating the phone on a five-point scale. The search task involved searching through a number of opinionated hypothetical reviews written by customers concerning the phone. The reviews ranged on a five-point scale from highly negative to highly favourable. In order to generate a measurable initial disposition, participants were asked to provide an initial rating based upon limited specifications, before asking them to examine the opinionated reviews. This may result in different selective exposure between different preliminary raters. Also, participants who were asked to provide an initial rating may demonstrate different patterns of information exposure, compared to a control group that viewed the same specifications but did not provide an initial rating. Although the control group did not outwardly provide a rating, they may have formed a disposition nonetheless. Therefore, a second control group was used that did not even view the specifications prior to the information search.

Thus, there were three groups that differed in their experience prior to information searching. Preliminary raters (PR) viewed specifications and then provided an initial rating.

Specification-only controls (SOC) viewed specifications but did not rate the phone. Finally, No-experience controls (NEC) neither viewed specifications nor rated the phone. I predict that preliminary raters should be most likely to form a more concrete initial disposition. This group should therefore demonstrate more selective exposure in line with the Evan's (2007a) three hypothetical thinking principles. Furthermore, based on the simulations in Chapter III, this increased selective exposure should result in the satisficing principle being met based on less information overall, and possibly, therefore, faster deliberation times.

Method

Participants

In total, 135 university students were recruited via an online advertisement and were rewarded with course credits. There were 96 female and 39 male participants; their ages ranged from 18 to 59 (M =21.94, SD = 6.05).

Design

There were three different between-subjects groups (Preliminary raters, Specifications-only controls, and No-experience controls). There was one within-subjects independent variable, the type of opinionated review, of which there were five levels. 1-Star opinions hated the phone and reported its worst features in their reviews. 2-Star opinions did not like the phone and mainly reported its bad features. 3-Star opinions thought the phone was okay and reported equal amounts of positive and negative attributes. 4-Star opinions liked the phone and mainly reported its good attributes, and 5-Star opinions loved the phone and only reported its good attributes. Three reviews were written for each type of opinion resulting in 15 items of information for the decision-maker to search through. The initial rating by the preliminary-rater group and the final ratings by all participants were recorded. Thus it is possible to observe any differences in search pattern by both how participants finally rated the phone and how preliminary raters first rated the phone. The number of reviews selected for reading in each opinion type and the amount of time spent reading each review was recorded.

Procedure

Participants were undergraduate students at the University of Southampton rewarded with course credits. They were given an information and consent form prior to each task (see appendix A for an example) and were fully debriefed after the experiment. The experiment was carried out in an experimental laboratory. All groups were informed that they were to evaluate a cell phone. The preliminary-rater group and specifications-only group were presented with a screen showing a picture of the mobile phone and non-opinionated specifications about its size, weight, battery time etc. (Figure 1). They clicked on an arrow when they were ready to continue. The preliminary raters were then shown a screen asking them to provide a preliminary rating of the phone. They were then taken to the review menu page. The specifications-only control group skipped the preliminary rating page and went straight to the review menu. The no-experience controls were taken straight to the review menu and were not shown the specifications or the preliminary rating page.

Figure 1. The stimulus of the phone and the specifications

The review menu displayed 15 boxes, with each box representing one of the 15 reviews in a 3 x 5 grid with the five opinion types clearly identified across the top and the three reviews of each positioned vertically underneath each other. So, for example, to view the second review by the user who thought the phone was “okay” (3-stars), the participant would click on the second review down in the third column. After reading a review the participant clicked on the arrow, which led back to the review menu. The program recorded which reviews were read and for how long. Participants in all groups could click on and read as many reviews as they liked until they were satisfied, whereupon they clicked on the arrow at the bottom, which took them to the final rating page. Here the participants were asked to make their evaluation of the phone on the five-point scale, indicated by stars.

Materials

The image and the specifications of the mobile phone were fabricated for the study (see Figure 1 for an example). Each review was the same length, of 100 words. This allowed us to compare reading times between reviews. The following is an example of a 1-star review See Appendix D for more details.

<u>1 Star- “Hated the Phone” Review 1</u>

"I absolutely hated this phone. I used to have a nice top-of-the-range phone but had to use this as an interim measure. It was a big step down from what I was used to. It was bigger and heavier, which was surprising as there was less in it, and it looked ugly. I also found it difficult to use in loud environments because the sound quality was so bad. In the end, I got rid of it as soon as I could. I would never get one of these again! Don't buy this phone, it is absolutely horrendous!"

Results and Discussion

Descriptive Statistics

One hundred and thirty-five participants were recruited with the greatest number in the preliminary rater group. This larger preliminary rater group was recruited to allow analysis between different preliminary ratings. Table 1 shows the number of participants in each group and their mean preliminary and final ratings. A one way ANOVA showed no significant difference between the groups in their final rating, $F(2, 134) = .661$, $p > .05$.

Table 1. Participants recruited for each group and their mean preliminary and final ratings out of 5 stars

	Number of Participants	Mean Preliminary Rating	SD Preliminary Rating	Mean Final Rating	SD Final Rating
Preliminary Raters	60	2.77	.65	2.83	.668
Specification-Only Controls	28	-	-	2.75	.645
No-Experience Controls	47	-	-	2.94	.763
All Groups	135	2.77	.65	2.85	.697

Exploration of search patterns — Measures of the Selective Exposure

This analysis examined the distribution of search patterns between the preliminary raters, the specifications-only controls, and the no-experience controls. As the initial concern was in regards to the valence selectivity of their total search time, we examined the proportion of reviews read in each opinion category by each participant. So, the proportion of 1-star opinions read for each participant would be the total number of 1-star reviews that they read, divided by the total number of reviews read by that participant. This controls for the predicted variances in volume between groups or individuals.

Figure 2 (top left graph) displays the proportion of reviews selected for reading based upon the experience prior to the search task. The results appear to demonstrate a consistent quartic (w-shaped) search pattern across all groups. This was supported by a 2-

way, mixed-design, repeated measures ANOVA which compared the different groups (preliminary raters, specification-only controls, no-experience controls) by their search pattern (proportion of reviews read from each category). The first part of the analysis found a significant overall effect of star rating on the proportion of reviews read across all groups (search strategy), $F(3.46, 456.12)$[6] = 15.50, $p < .001$. Bonferroni post hoc tests confirmed the quartic pattern revealing significantly more reviews read in the 1-, 3- and 5-star categories than in the 2- and 4-star categories ($p < .001$ for all). No other comparisons were significant.

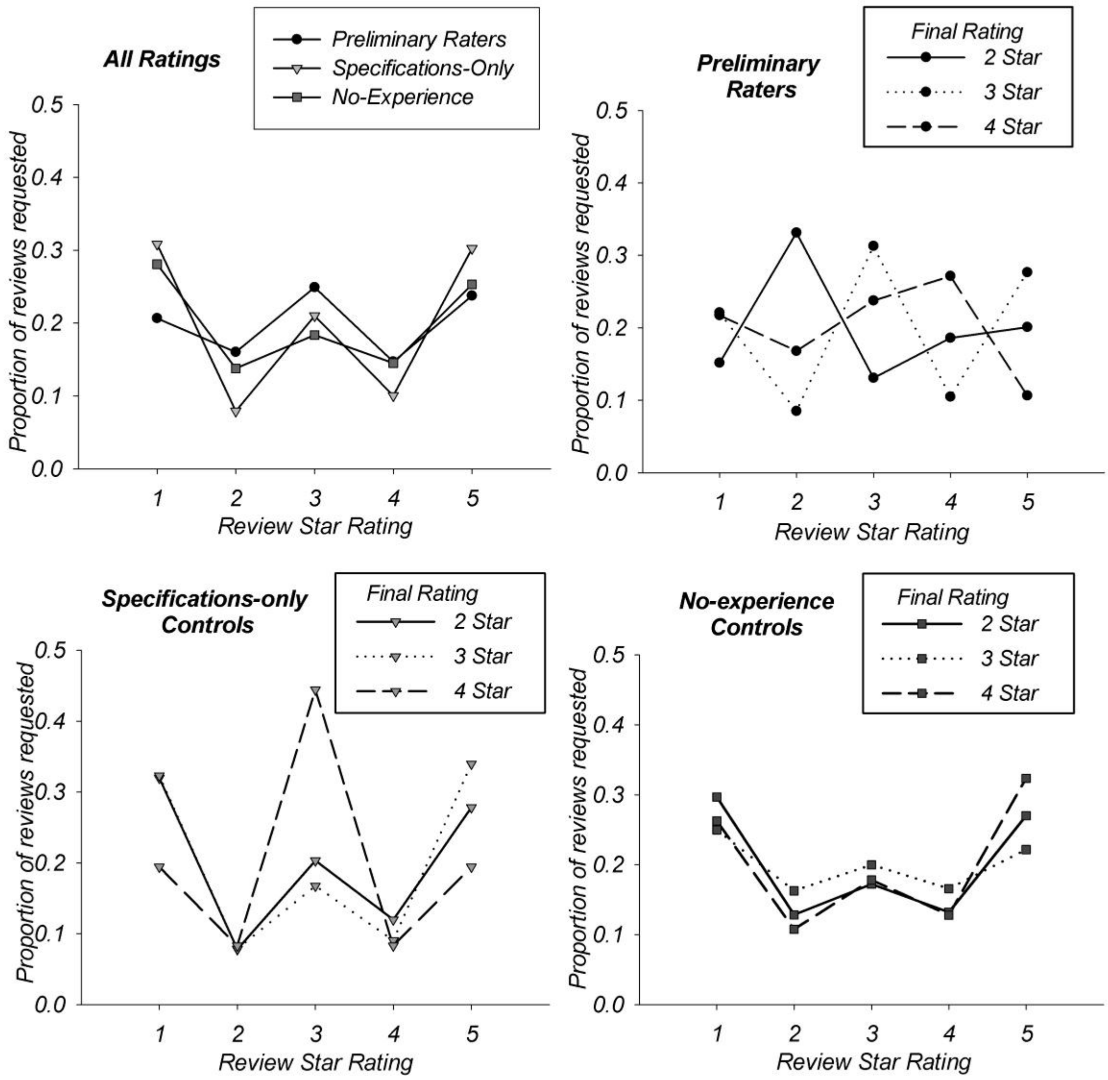

Figure 2. The top left panel displays the overall search pattern distributions of the three groups. The other panels display the three groups separately, showing their search patterns according to their final rating.

[6] Degrees of freedom were corrected for all ANOVA tests using Greenhouse-Geisser correction due to a violation of the sphericity assumption.

There was also a significant interaction between the search pattern and three groups (preliminary raters, specification-only controls, and no-experience controls), $F(6.91, 456.12)$, = 2.08, $p < .05$. This indicates that there may be some effect on information selection depending upon the experience prior to the main search task. The quartic search pattern in Figure 2 (top left panel) indicates a degree of selective exposure by all groups, not in the sense of search biased by an initial tendency, but selective in the sense of sampling central and extreme cases more than others.

A 2-way, mixed-design, repeated measures, ANOVA was performed on the controls data (both groups) to explore their search patterns alone. The test revealed a significant difference across reviews $F(3.05, 222.36)$, = 24.97, $p = .000$. Bonferroni post hoc tests confirmed the quartic pattern revealing significantly more reviews read in the 1- and 5-star categories than in the 2-, 3-, and 4-star categories ($p < .001$ for all). In addition, significantly more reviews were read in the 3-star category than the 2-star ($p < .01$) and 4-star ($p < .04$) category but also significantly less than the 1-star ($p < .01$) and 5-star ($p < .05$) category. However, no significant difference between the two control groups in their overall search pattern was found, $F(3.05, 222.36)$, = 1.98, $p > .05$. As there was no difference between controls in terms of their overall search patterns, both were combined into one control group. A further 2-way repeated measures ANOVA found a significant difference between preliminary raters and combined controls in their overall search pattern $F(3.33, 436.11)$, = 3.16, $p < .05$. This indicates that, based on the search pattern, there is a significant effect of making a preliminary rating on subsequent information exposure.

In order to determine where these effects might lie, all three groups (preliminary raters, specification-only controls and no-experience controls) were divided into further subgroups based upon their final rating. As only two participants finally rated the phone with one star and no participants rated it with five stars, these participants were excluded from the subsequent analysis. Figure 2 (top right and bottom graphs) shows the search patterns by each group and their final ratings. A three-way, mixed- design, repeated measures ANOVA was performed on the data revealing a significant interaction between the group and the search pattern depending on the final rating, $F(13.78, 427.08)$, = 2.62, $p < .001$.

From Figure 2 it is clear that when participants are asked to make a preliminary rating, their search patterns are significantly different than if they simply viewed some specifications or have no experience. Specifically, the quartic pattern is replaced by selective exposure which strongly relates to the final judgement. To determine how the preliminary rating affected the participants' selective exposure, the preliminary raters were also explored by themselves. A 2-way repeated measures ANOVA examining the differences between the preliminary raters showed that they exhibited significantly different search patterns based upon their initial rating, $F(8, 220) = 5.410$, $p = .000$. A further linear regression analysis determined that the initial rating was highly predictive of final rating, $F(1, 59) = 110.49$, $p < .001$, $R = .81$.

The results confirm that providing initial ratings changed the way subsequent information was sought. However, this analysis does not reveal precisely what information was important to preliminary raters. Thus a subsequent analysis was performed, ordering the information depending on whether the review rating would have least dissonance (align with the preliminary rating), most dissonance (furthest distance from the preliminary rating), or reside somewhere in between.

The means, shown in Figure 3, were compared using a repeated measures ANOVA, which found a significant effect of the distance between the preliminary rating and the review valence on the proportion of reviews read, $F(2, 118) = 12.44$, $p < .001$, which appears as a U-shaped relationship. Indeed, Bonferroni post-hoc t-tests revealed that, while there was no significant difference between the number of most dissonant and least dissonant reviews asked for ($p > .05$), significantly more information was sought in the least and most dissonant categories than in the categories between these two poles ($p < .001$ for both).

I argue that these results demonstrate the use of selective exposure. The results are in line with Evans' (2007a) hypothetical thinking principles as only evidence which directly related to the current hypothesis is examined. Given no initial disposition (no-experience controls) or a possibly weak or undefined one (specifications-only controls), selectivity appeared more driven by the task structure. Thus, the quartic search strategy of the controls represents attention to information that appears as if it would increase the coherence of the representation, that is, increase differentiation of opinions. This is achieved by viewing the worst and the best reviews and to a lesser extent a middle anchor point. The 2- and 4-star reviews act to undermine this coherent differentiation of opinions and so they tend to be ignored.

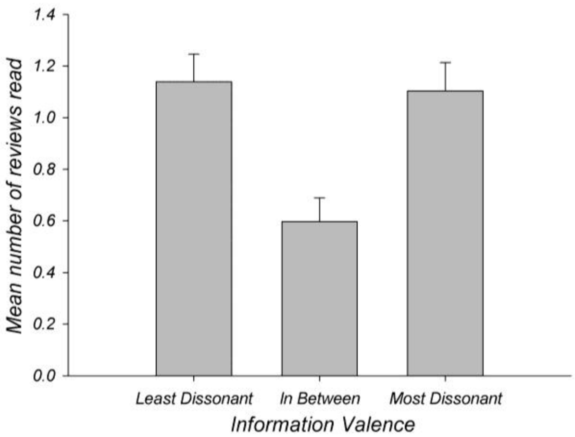

Figure 3. Mean number of reviews read by preliminary raters depending upon the distance between the preliminary rating and the valence of the review

It seemed that a stronger, or at least more defined, initial disposition is formed through a preliminary rating. Now, following the dual-process account, the only relevant information is the strongest evidence for the hypothesis and the most dissonant evidence (i.e. strongest evidence for and against the individual's initial hypothesis). This finding is in line with both the dual-process account and the theory of cognitive coherence.

Effect on Decision Time — Type 3 Processing Effects

Figure 2 shows that preliminary raters' search patterns differ from the control's quartic trends, suggesting some change occurring in the approach evaluators have to collecting evidence after providing an initial rating. As selective exposure may be a tool to increase cognitive coherence, it was hypothesised that this may also have a measurable impact on decision times. In order to examine volume differences in evidence collection, I examine the total amount of information sought as a function of group (preliminary raters, specifications-only controls, and no-experience controls). The results are shown in Table 2. Simulation 2 in Chapter III, based on the sequential sample model, predicts that the more selective the exposure to information, the quicker the overall search time should be.

The results of a one-way independent ANOVA demonstrate that for the "mean total time spent information searching" dependent measure there was a significant effect of the experience prior to information searching $F(2, 132) = 6.75$, $p = .002$, with the preliminary-rating group taking the least amount of time. For the mean total number of reviews read dependent measure there was also a significant effect of initial experience, $F(2, 132) = 3.89$, $p = .023$, with the preliminary-rater group reading fewer reviews. Bonferroni post-hoc tests revealed a significant difference between the preliminary-rater group and the no-experience control group for both dependent measures ($p < .001$, $p < .05$ respectively). The specifications only control was not significantly different from either group in either measure ($p > .05$ for both) although a significant linear trend was found across groups for the dependent measures ($p < .05$ for both).

These results indicate that a preliminary judgement (which is associated with strong selective exposure) leads to quicker decisions based on fewer items of information, compared to a control with no experience. Due to a lack of statistical difference between the specification-only group and the others we cannot be sure whether the volume difference is due to forming an initial judgement or simply viewing evidence. Nevertheless, these results are still important as they demonstrated that the amount of information required at the review stage is dependent on initial experiences. This quicker decision time is precisely what would be expected if a decision threshold was being met faster due to the satisficing principle being met at a faster rate than controls (see simulations 1 and 2 in Chapter III).

Table 2. Total time (in seconds) and amount of information sought prior to the final rating depending on initial experience

	Mean total time spent information searching (sd)	Mean total number of reviews read (sd)
Preliminary Raters	45.98 (36.20)	4.42 (2.86)
Specification-only Controls	56.32 (48.62)	4.96 (3.31)
No-experience Controls	74.72 (39.74)	6.13 (3.45)

General Discussion

In summary, the control groups demonstrated a strong preference to explore the 1- and 5-star ratings and, to a lesser extent, the 3-star ratings. The no-experience controls sought the most information in the review stage. The preliminary rater group was biased towards reading reviews with the same star rating as the participant's initial judgement, but this group also examined the most dissonant information. Furthermore, this selective exposure that was specific to that preliminary rating was observed, a between-subjects selectivity effect. These results are in line with the dual-process framework and, in particular, Evans' (2007a) three hypothetical thinking principles indicating that dual-processes may have a role to play in theories of biased predecision processing.

The results of this study also support a more cognitive (i.e. dual-process or cognitive coherence approach) rather than motivational (cognitive dissonance) approach to biased predecision processing when only a single item is involved. The study demonstrated that individuals would prefer information that was related to the hypothesis they were considering (i.e. strongly confirming and strongly dissonant, but little in between). The consideration of strongly dissonant information appears to go against the motivation-based theories. Most recent studies have found biases in selective exposure towards confirming information (Jonas, et al., 2001; Pinkley, Griffith, & Northcraft, 1995; Lundgren & Prislin, 1998; Frey, 1981; Johnston, 1996), a view which supports the motivational and cognitive explanations. Interestingly, early studies also found that people were frequently interested in dissonant information. For example, Gerard (1967) found that participants spent more time looking at the alternative they eventually rejected than the alternative they accepted. Indeed, in a study during the 1964 American Elections, participants were offered brochures supporting either their favoured candidate or his rival (Lowin, 1967). When the arguments in the sample were strong, it was found that participants ordered more brochures from their candidate. However, when the arguments in the sample were weak, it was found that participants were more likely to select brochures from the rival (Baron, 2008). In a similar study, Albarracin and Mitchell (2004) investigated the relationship between attitude strength and selective exposure. Specifically, it was found that participants who felt confident in their ability to defend their argument were more likely to select dissonant information. However, if this motivational explanation was the case, I would have expected individuals to avoid the strongly dissonant information and perhaps consider weakly dissonant information. In the study this was not the case, as weak dissonant evidence was ignored in favour of the strongly dissonant evidence. The dual-process explanation, however, does not suffer from this problem. The dual-process account would predict that individuals would be more inclined to consider consistent information first just as the motivational explanation. However, if the satisficing criterion is not met by early deliberation and more complex type 2 reasoning is engaged, the dual-process account would also predict (as found in the results) that individuals may be inclined to test the hypothesis by exploring the most relevant dissonant information (the strongest opposite opinion). Therefore, at least for the evaluation of single novel items, I find that a dual-process account has a stronger argument for the explanation of these results. Interestingly, while these dissonant reviews were examined individuals rarely changed their opinions, as the initial rating was highly predictive of the final rating (R^2 = .81). Thus, although individuals were inclined to read the opposite reviews, it is possible that some degree of biased interpretation was involved as well.

The focus towards type 3 processing is a novel step in understanding biased predecision processing. The results were in line with predictions based on the simulations in Chapter III. The total amount of information gathered appeared to depend on the degree of selective sampling of evidence resulting in faster decisions based on less information when selective exposure occurred most strongly (preliminary raters). This appears to show some value in the sequential sample model described in Chapter III and that the consideration of deliberation times as a measure of the effects of type 3 processing may be useful in this domain.

Future Directions

On the basis of this study it is possible offer some considerations of future studies. The study demonstrated that preliminary ratings influence selective exposure. However, it would be interesting to determine how initial dispositions are formed during single item evaluation. Perhaps a study could provide different sets of specifications, presenting either a strongly positive or negative first impression, and explore whether selective exposure similar to the preliminary raters can be observed without the need for an initial rating. Another example would be to explore whether there is a difference between search patterns based upon the source of bias (e.g., either by oneself or by another). It would be interesting to explore the extent to which other examples of biased predecision processing appear to be motivationally or cognitively driven.

A major limitation of the sequential sample model was that it summarizes selective exposure in quite a course manner. It simply increases drift rates (see simulation 2) under selective exposure. However, the dual-process explanations are far more nuanced involving the singularity and relevance principles. Therefore, there is a clear gap between the sequential sample model and these important dual-process concepts. On the basis of this study I see these as important factors in JDM, I believe that further development of the sequential sample model could be made with respect to this issue. Indeed, in Chapter VII, I discuss how I believe that these two principles may be integrated into the model.

Another potential limitation with this study is that we inferred reading from the interval between clicks on the screen. This has clear limitations and a more effective means might be to replicate considering more sophisticated techniques such as eye tracking monitors. Finally, the study explored a novel contribution to selective exposure, through the examination of deliberation time and differences in the volume of information sought. The focus towards type 3 processing highlights the potential benefits of dual-process theory in biased predecision processing research. Further studies might examine different predictors of differences in the volume of information sampling and decision thresholds. That is, when do we decide to stop searching for evidence and make a judgement depending on different initial dispositions or tasks? Also, it might be important to explore how much information is normatively optimal in different scenarios.

Conclusion

In Chapter III, I noted that the sequential sample approach had clear application to studies of biased predecision processes (Brounstein, 2003) and selective sampling of information described in Chapter I. While these studies had explored the types of evidence gathered when biased precision processing occurs, I was unaware of any that have also focused on the amount/volume of information required when biased predecision processing occurs. In Chapter IV, therefore, I aimed to tackle whether the dual-processes, and in particular the sequential sample model simulations, could apply to this topic. The study in this chapter explored this issue demonstrating that the early information available to decision-makers appears to impact heavily on the evidence that they choose to examine and the total amount of evidence they appear to require in judging the item. Despite little in the way of obvious motivational reasons, individuals who formed preliminary ratings based on the early information appeared to demonstrate selective exposure. This can be explained using a dual-process approach, in particular, the three principles of hypothetical thinking (Evans, 2007a). These findings support the view that dual-process theory is beneficial in understanding the JDM. Furthermore, the results align with the predictions based on the simulations in Chapter III providing support for the sequential sample approach to default interventionism and the role of the type 3 processing in JDM.

Summary Points

- In the domain of biased predecision processing, dual-process explanations relating decision processes have been somewhat neglected in favour of motivational accounts.
- In this experiment, I show evidence of biased predecision processing in a task which might not be expected to produce such a bias under the current motivational accounts. Indeed, the motivational accounts do not seem to represent the findings of examining strongly dissonant information. However, a dual-process account could explain the results.
- The biased predecision processing literature does not consider deliberation time/evidence volume as a measure of early informational biases. However, the simulations in Chapter III indicate that evidence volume may be related to selective sampling of information. This experiment took the novel step of assessing the amount of evidence gathered as a way of testing the model and an indication of evidence for type 3 processing in biased predecision processing.

- The sequential sample model correctly predicted that increased selectivity of information should tend to be associated with a decrease in the amount of evidence examined and the correlated measure of deliberation time.
- However, the experiment also showed an important limitation with the sequential sample model, in that it could not represent the nuances associated with this selective exposure as it currently models evidence gathering simply by an average drift rate. This limitation is addressed in Chapter VII.

Chapter V – Empirical Chapter

"*Thinking isn't agreeing or disagreeing. That's voting.*"
- Robert Frost (American poet, 1874-1963)

The previous study demonstrated some initial support for the sequential sample model by predicting how selective exposure to information can impact on evidence volumes and deliberation times (evidence of type 3 processing) in line with the simulations in Chapter III. However, this was only one of the predictions based on the simulations. I also argued that the sequential sample model could also account for manipulations of type 3 processing, thereby predicting the extent to which early type 1 versus and late type 2 processing should impact on choices based on manipulations of a satisficing threshold. In particular, I proposed that the effect of time pressure could be accounted for via the concept of a satisficing threshold in a sequential sample model and that increased reliance on default, type 1, responses could be modelled in this fashion. Indeed, one of the main features of the sequential sample model is how it accounts for a congruency effect of type 1 and type 2 processing in choice accuracy, a prediction that will be tested in this chapter.

Importantly, while time pressure has been shown to result in an increase in biases associated with type 1 processing generally, the use of a sequential sample model to represent this effect has not been attempted. As outlined in Chapter III, one of the key benefits of this quantitative approach is that it is not restricted to diametric predictions (i.e. present versus absent categories of time pressure), rather it is able to make predictions along a range of time pressure levels. Therefore, it is possible to examine whether the sequential sample model predictions of choice behaviour over a range of levels of time pressure reflects empirical data. Specifically, this chapter seeks to assess the descriptive validity of the sequential sample model approach to dual-process congruency effects (i.e. the extent to which the model can reflect the empirical behaviour patterns relating to congruency effects) when type 3 processing is manipulated over a continuous (as opposed to diametric) range of time pressures. This serves to fulfil the aims set out in Chapter III regarding simulation predictions for the congruency effect and continuous predictions.

Bounded Multi-Attribute Decision-Making: Type 3 Processing and Time Pressure Mediating Type 2 Operations and Type 1 Responses[7]

Abstract

This study tests the sequential sample model predictions from Chapter III regarding the effect of a range of time pressures on type 1 and type 2 processing during decision making. Forty-six participants were required to make investment decisions under four levels of time pressure. In each decision, participants were presented with stereotype (type 1) cues which were either congruent or incongruent with the analytical (type 2) information. The congruency conditions allowed the examination of the extent to which decisions were based upon the type 1 vs. type 2 information, and to see if this was affected by the varying degrees of time pressure. As expected, the overall accuracy was reduced with greater time pressure and accuracy was higher when the stereotype and analytical cues were congruent than when they were incongruent. Consistent with past studies, the results showed that under high time pressure participants used more stereotype cues than at other time pressures. Importantly, the sequential sample model could account for the patterns of behaviour over the four levels of time pressure with reasonable effectiveness (measured by R-squared statistics). I see this as evidence for the sequential sample model having some future potential for predicting when, and to what degree, the effects of type 1 biases may be observed over varying degrees of time pressure.

Introduction

Some of the most important decisions we make are important because they are made under time pressure. Understanding how time pressure can affect choices, judgements, and conclusions, is an important topic for consideration. This chapter examines the relationship between time pressure and information usage and assesses the extent to which transitions in dual-processes may be modelled quantitatively. In particular, this study continues the exploration into quantitative modelling of type 3 processing, this time examining how we can model its role in the mediation of type 1 and type 2 processing.

Time Pressure

Time pressure is assumed to be experienced when the time available for the completion of a task is perceived to be shorter than normally required for the activity

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[7] Adapted from a published article: Fraser-Mackenzie, P.A.F. & Dror, I.E. (2011). Dynamic reasoning and time pressure: Transition from analytical operations to experiential responses. *Theory and Decision. 71(2),* 211-225

(Svenson & Edland, 1987). Research has shown that in response to time pressure we can: increase our processing speed of individual items, increase selectivity of information by both type and volume (Ben-Zur & Breznitz, 1981; Wallsten, 1993), and manipulate the strategies we employ (Payne, Bettman, & Johnson, 1993).

Due to these effects, time pressure can have a dramatic effect on our ability to make optimal judgements and increases human error (e.g. Freund et al., 1985; Kruglanski & Freund, 1983; Dror, Busemeyer, & Basola, 1999). Studies have demonstrated that individuals appear to rely on more simple reasoning strategies which are prone to cognitive biases such as: primacy effects in impression formation, anchoring in probability judgements (Freund et al., 1985; Kruglanski & Freund, 1983). A striking finding was the tendency to use more ethnic stereotyping (Freund et al., 1985; Kruglanski & Freund, 1983). One standpoint is that individuals appear to be forced to use simplified, suboptimal heuristics to compensate for the loss of the ability to perform normative strategies. This evidence was used to argue the case for motivated reasoning (Kunda, 1990), whereby contextual factors such as accuracy motivation and external pressures affect our decision strategies. An alternative to the motivational explanation is a cognitive explanation, based on dual-process theory.

As the default type 1 processing is quicker and more suited to providing answers when there is little time available, this type of processing appears to be relied on under increased time pressure. Whereas type 2 processing is better suited to situations in which there is adequate decision time. Therefore, it has be theorised that in response to time pressure and a general reduction in our ability to perform time consuming type 2 processes, the automatic type 1 processing responses may have a greater effect on our judgements and choices. Support for this view is found in the findings of increased belief bias under time pressure (Evans & Curtis-Holmes, 2005).

It is possible, therefore, that this may provide an explanation for increased used of stereotyping under time pressure (Kruglanski & Freund, 1983). Support of this view is found in early theories of stereotyping suggesting that stereotypes can occur spontaneously (cf. Bargh, 1999; Devine, 1989). Subsequent research showed that measures of stereotype impressions depend on the prejudice, goals, cognitive resources, and learned associations of the individual (Gilbert & Hixon, 1991; Kawakami, Dovidio, Moll, Hermsen, & Russin, 2000; Lepore & Brown, 1997; Sinclair & Kunda, 1999). These findings strongly echo the default-interventionist account that the stereotypes, as a type 1 response, may depend on a combination of strength of initial type 1 response and in particular the role of type 3 processing and the satisficing principle. The aim of this study is two-fold. Firstly, the study will investigate the relationship between time pressure and the use of stereotype information over more analytical information. Secondly, it will investigate the extent to which the simulation predictions, in Chapter III, regarding the relationship between satisficing threshold manipulation (time pressure) and the congruency of type 1 and type 2 information on choice accuracy, reflects the relationships observed in the empirical data.

A Model of Dynamic Reasoning

In Chapter III, I introduced a sequential sample model which aimed to capture this shift between the two types of processing based on some of the concepts of default-interventionism. The general prediction is that given a high decision threshold (i.e. under no time pressure), more type 2 evidence accumulation is possible and the initial type 1 bias has a smaller overall impact resulting in a more analytical approach across participants. However, if the analytical, type 2 processing is limited by a lower decision threshold (i.e. under time pressure), then the early, type 1 processing will have a greater overall impact on the final outcome representing a greater reliance on stereotyping approach across participants. As discussed in Chapter III, the effect of the type 1 processing of stereotype information may be represented by the initial preference state, z, parameter. This may be seen as the resting activation of the deliberative system before analytical processing begins. The effect of time pressure may be modelled using the threshold, θ, parameter which limits the amount of analytical evidence collected. The interaction between these two parameters, z and θ, represents the likelihood that choices will be more predicted by type 1 vs. type 2 cues.

In summary, the modelling mechanism involves type 1 activation of stereotyping information as a default response, but the predictiveness of that type 1 response depends whether there is enough time for type 2 processing intervention. As type 3 processing allows only as much type 2 processing as required, or is allowed by environmental constraints, time pressure can be modelled via the satisficing threshold parameter. This mechanism strongly echoes the view that stereotypes that are activated initially can be reduced over time as “interaction” (type 2 processing) occurs (Kunda, Davies, Adams, & Spencer, 2002). Thus, as Kunda points out, there is a difference between *stereotype activation*, i.e. type 1 processing occurring, and *stereotype application*, i.e. type 1 processing playing a role in choice, (Kunda & Spencer, 2003).

Given this theory, it is possible to make predictions concerning the effect of congruency between type 1 and type 2 cues on decision outcomes using a sequential sample model to represent this dynamic reasoning process under various levels of time pressure. Simulations 4 and 5 in Chapter III demonstrated the predicted effect of congruency of type 1 and type 2 processing responses under a single threshold level. The purpose of this study is to investigate whether the magnitude of the congruence effect in empirical data reflects the model estimates based on satisficing thresholds by time pressure.

In studies of time pressure, participants are usually only presented with two levels of time pressure: present and absent. This diametric methodology only has the ability to display the two ends of the transition process, so providing a polarised view of the relationship between time pressure and the relationship between type 1 and type 2 processing. This study aims to explore this relationship more fully by using more levels of time pressure. The aim therefore, is to establish whether the predicted choice characteristics based on the sequential sample model reflect those found in the data. It is hoped that this will reveal more than the traditional studies of time pressure while also testing the descriptive validity of the model.

Experiment

The study offered participants a number of two-choice investment proposals. Each choice had eight cues which could be used to make the decision. One cue was a more type 1 orientated cue; a positive or negative picture of the company boss. The rest of the cues were more type 2 processing orientated; numerical attribute information which could be compared using analytical operations. The methodology went further than other studies by exploring how strategy usage changes over a number of levels of time pressure rather than simply examining the two ends of the spectrum.

Method

Participants

A total of 46 undergraduate students were recruited via an intranet website and were rewarded with course credits. There were 35 female and 11 male participants and they were between the ages of 18 and 29 years (M =19.85, SD = 2.39).

Design

The participants were asked to decide which of two investment proposals they felt would be most beneficial to them (see Figure 1 for an example) on each trial. Each investment figure (row 1) ranged between £14,000 and £170,000. Each return (row 2) was 3.4 times the investment on all occasions. The years of experience (row 3) ranged between 1.7 and 15 years. Participants were instructed that the years of experience were positively related to chance of success. The credit rating (row 4) ranged between one and nine, low numbers indicating poorest credit rating and high indicating good credit rating. Participants were instructed that credit rating was positively related to success. The percentage market share (row 5) ranged between 5% and 95%. Participants were instructed that market share was positively related to chance of success. The number of competing companies (row six) ranged between one and ten. Participants were informed that the number of competing companies was negatively related to chance of success. Finally, a copyright (percentage of the world) (row 7) ranged between 5% and 95%. Participants were informed that this was positively related to chance of success.

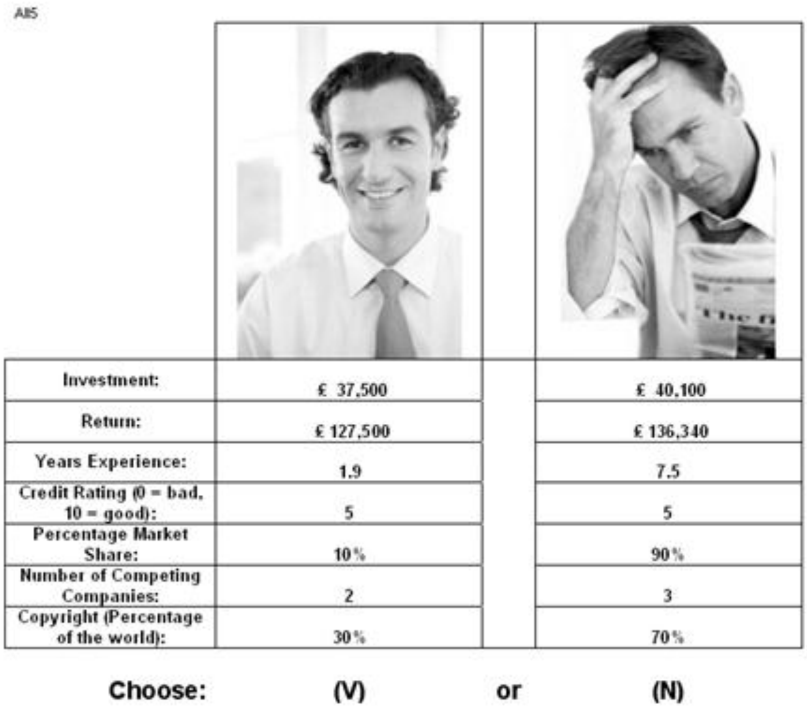

Figure 1. An example of a trial

The intended dependent measure of strategy usage was the accuracy of choices compared to the rational choice. Accordingly, counterbalancing was used to ensure that the same level of accuracy could not be achieved through simple heuristics, i.e. just choosing one or two factors, or through systematic guessing (e.g. always selecting the left option). The trials were counterbalanced as follows. Each return was 3.4 times greater than the investment figure and the highest return was counterbalanced within participants to be congruent with the optimal solution on half of the trials. In all investment choices, one investment was better in three out of five of the other data factors (*success factors*), equal on one factor, and worse on a fifth. These values were counterbalanced between trials using a 5x5 latin square design so that a participant could not use one factor to perform at an optimal level. In addition, whether the optimal solution was on the left or the right of the trial was also counterbalanced. There were four trial blocks, A, B, C and D, each containing 20 trials. Each block was used for a level of time pressure, and the order of the blocks was counterbalanced between participants leading to 24 permutations. This meant that we could be sure that it was time pressure, and not differences in complexity of the trial blocks, which caused any effect found.

Despite the careful counterbalancing, the design does not account for systematic weighting of cues in the decision space. It may be quite possible that different people perceive certain attributes to be more important than others whether or not they have high validity within the trial set. In order to overcome this potential problem participants were paired so that two participants saw exactly the same order of blocks and hence the same analytical cues in the exact same order. It was expected that the more type 2 processing that was employed (i.e. driven by analytical cues), the greater the level of agreement between pairs on the same trials where there might not be between participants across different trials, due to this weighting issue.

In addition to the analytical cues, participants were also shown a stereotype cue. This cue was a picture of the businesses CEO which was either positive (smartly dressed business person appearance) or negative (stigmatised or stressed appearance). As mentioned, each pair of participants saw the same analytical cues in the same order. However, the exception was the stereotype cues which were switched. These stereotype cues were counterbalanced between the pairs so that the positive picture was congruent with the normatively optimal solution in only half the trials and one of the pairs had a congruent trial while one had an incongruent trial. The result is that if participants only employ type 1 processing and ignore the analytical (type 2) cues then we should observe greater disagreement between pairs.

Recall that time pressure is said to be experienced when the time available for the completion of a task is perceived to be shorter than normally required for the activity (Svenson & Edland, 1987). Time pressure, then, is an intrinsically individual experience. Therefore, individually adjusted time pressure levels were employed in an attempt to push subjective, individual, experiences of stress as close together as possible. Participants underwent five practice trials of which the last three were recorded and the mean time was taken to use as their individual *base decision time*. This acted as a way of metering the time pressure levels in each block to that individual participant. In low time pressure, 40% of their base decision time was removed. In medium time pressure, 65% of their base decision time was removed. In high time pressure, 80% of their base decision time was removed.

The main dependent measures were the agreement between pairs and the accuracy rates compared to the normative solution. Participants were asked to report how confident they were with each decision they made on a 7-point scale (1 = no confidence to 7 = total confidence).

Procedure

Participants were undergraduate students at the University of Southampton rewarded with course credits. They were given an information and consent form prior to each task (see appendix A for an example) and were fully debriefed after the experiment. The experiment was run on a computer program in an experimental laboratory which could present the choices as picture stimuli and record responses made on the keyboard. Participants read information explaining all the terms and figures used in the decision tasks in layman's terms and participants were encouraged to ask any questions they had concerning the task. Participants then underwent the five practice trials to measure their base decision time and the computer program worked out the individual time pressure for each block for each participant. Each of the four blocks, one for each level of time pressure, contained 20 trials totalling 80 trials per participant. Participants made their responses via a keyboard by pressing "V" to choose the left option or "N" to choose right option. Under time pressure, the choice task was displayed for the allotted individual time pressure value and then the information was hidden and they were asked to make their choice as soon as this occurred. Under the no time pressure task, the choice stimulus was displayed until they made their choice. After each choice was made, participants were asked to report their confidence on the 7-point scale.

Modelling

The probability of choosing choice *x* over choice *y* for a sequential sample model was as follows (from Busemeyer and Townsend, 1993).

$$p(x,y) = \frac{\exp[4 \cdot (\frac{d}{\sigma}) \cdot (\frac{\theta}{\sigma})] - \exp[2 \cdot (\frac{d}{\sigma}) \cdot (\frac{\theta - z}{\sigma})]}{\exp[4 \cdot (\frac{d}{\sigma}) \cdot (\frac{\theta}{\sigma})] - 1} \qquad [1]$$

Where *d* represents the valence difference, i.e. the mean change in preference produced by each new sample of the information, σ^2 represents the variance of that valence difference, θ is the decision threshold, and *z* is the initial bias from type 1 processing (see Chapter III for more information). The model was fitted to the agreement data using a grid search in R to determine the parameters which minimized the root mean squared error (RMSE) of prediction of the aggregate choice proportions. The best fitting parameters for preference state drift was as follows: d = 3.12, σ = 5.50. The time pressure thresholds were determined using the following:

$$\theta_i = k_i(\theta_{noTP}) + c \qquad [2]$$

Where k *is* the proportion of the base decision threshold at no time pressure and c is a constant, c = 1.98. For the base decision threshold (no time pressure), θ_{noTP} = 15.98. So for low time pressure (40%), k = .6, θ_{lowTP} = 11.57; medium time pressure (65%), k = .35, $\theta_{mediumTP}$ = 7.57; high time pressure (80%), k = .20, θ_{highTP} = 4.29. The type 1 bias was represented by the initial bias; for congruent trials z =.46, for the incongruent trials z = -.46. Recall from Chapter III that z was the initial distance already travelled towards/away from each of the decision threshold prior to beginning type 2 operations.

Results

Figure 2 shows the accuracy of choices for situations where the experiential and analytical cues were congruent and incongruent. It also shows the predictions of the sequential sample model. The model appears to reflect the mean behaviour fairly well. Figure 3 shows the model predictions alongside each participant's choices. The R^2 values show that the model is relatively effective at describing the data. The figures appear to show a greater effect of time pressure on accuracy in the incongruent condition than in the congruent condition.

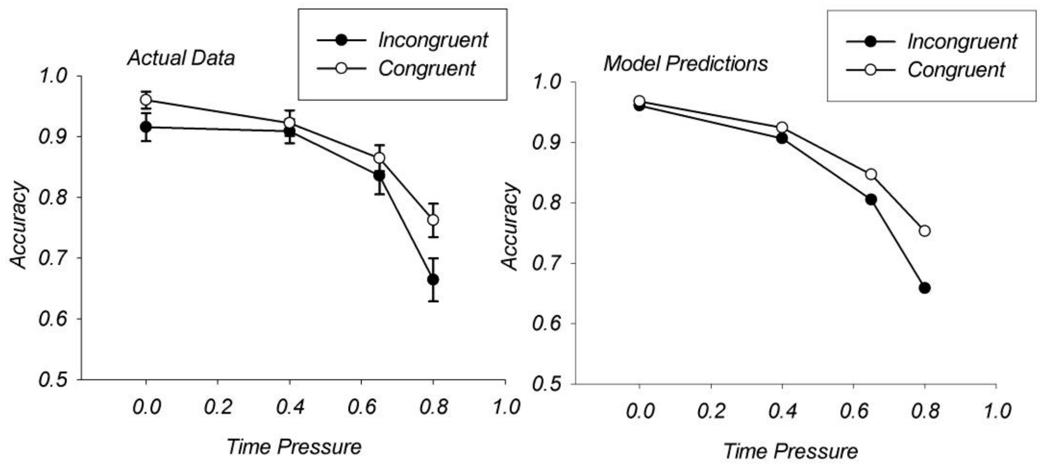

Figure 2. The effect of time pressure on accuracy under congruent and incongruent conditions. Time pressure is shown as the proportion of the individual participant's base decision time removed in each condition.

A two-way repeated-measures ANOVA showed that as time pressure increased, accuracy decreased, $F(1.79, 79.07^{8})$ = 58.13, p < .001. Bonferroni post hoc tests showed that while there was no significant difference between the no time pressure and low time

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[8] Degrees of freedom were corrected for the ANOVA test using Greenhouse-Geisser correction due to a violation of the sphericity assumption.

pressure trials ($p > .05$), all other comparisons were significant ($p < .05$). Furthermore, the ANOVA showed that there was an effect of experiential cue congruency on accuracy rates. In that, when the picture cue was congruent with the optimal solution, participants performed better than when the picture was incongruent $F(1, 44) = 4.82$, $p < .05$. Despite Figure 2 appearing to show an interaction, the ANOVA did not find a significant interaction between time pressure and congruency on accuracy, $F(2.6,144.4) = 1.95$ $p > .05$. However, at this stage we do not have any information regarding the types of cues used in each level of time pressure.

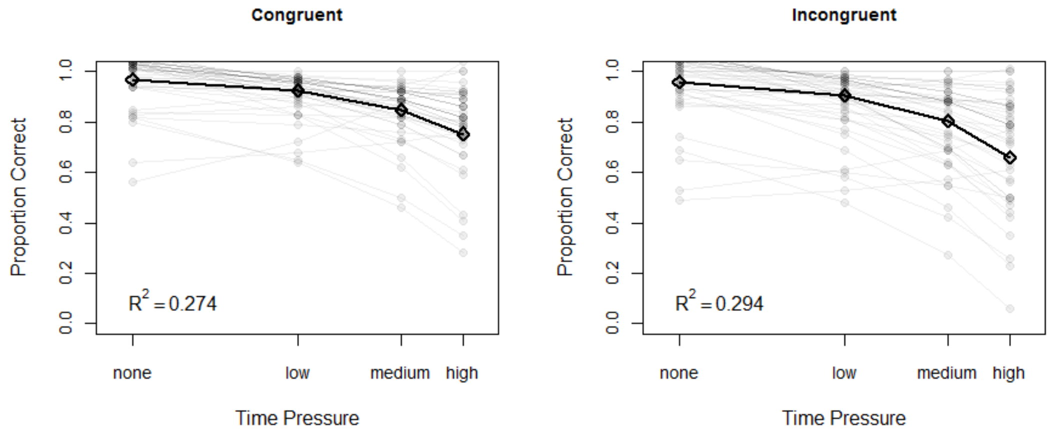

Figure 3. The model predictions (dark thick line) alongside the best fitting lines for individual participant data (light thin lines). R^2 values for the congruent and incongruent conditions are shown in the figure.

In order to estimate how individuals used the range of analytical cues and stereotype cues in this experiment, the mean choices (i.e. “V” or “N”) for each trial were regressed by the different choice attributes (cues) for each level of time pressure. After excluding the investment cue, the model accounted for a significant amount of the variance in the participants’ choices; (R^2=.949) $F(7,159) = 404.0$, $p<.001$, under no time pressure; (R^2=.919) $F(7,159) = 247.1$, $p<.001$, under low time pressure; (R^2=.827) $F(7,159) = 103.8$, $p<.001$, under medium time pressure; and(R^2=.596) $F(7,159) = 32.0$, $p<.001$, under high time pressure.

The cue utilisation data (Table 1) shows that a large number of cues were significantly predictive of the final decision in all levels of time pressure. However, despite many cues being used in all levels of time pressure, participants’ accuracy decreases (see Figure 2) as time pressure increases. Recall that the design controlled out single cues having high validity. If participants were all using the full range of cues in each trial decision at each level of time pressure, we should observe no significant reduction in accuracy across time pressure conditions. Therefore, we must assume that the accuracy rates (Figure 2) do demonstrate a reduction in the number of cues used, and that cue weight results (Table 1) demonstrate a degree of variation, between participants on the same trials and perhaps within participants across trials, in cue utilisation. Significantly, in contrast to the sequential sample model's predictions, it seems that the stereotype cue was also considered when there was no time pressure (see Figure 2 and Table 1). I shall return explain this finding in the discussion section of this chapter.

Recall that the participants were paired so that each pair viewed identical analytical cues in the same order but with disagreeing experiential cues. If my hypothesis is correct then we should also observe an increase in disagreement between pairs as time pressure increases (Table 2) as the use of stereotype cue diverges pair consensus. A repeated measures ANOVA showed a significant increase in disagreements between pairs as time pressure increased, $F(2.28, 50.10) = 34.82$, $p < .001$. Bonferroni post hoc tests showed that that while there was no difference between the no time pressure and low time pressure trials in agreement ($p > .05$), all other comparisons were significant ($p < .05$).

Table 1. The regression weights of the cues determined by linear regression.

Time Pressure	*Picture*	*Return*[1]	*Experience*	*Credit*	*Market Share*	*Competition*	*Copyrights*
None	0.041*	0.039*	0.423**	0.338**	0.399**	0.404**	0.527**
Low	0.020	0.039	0.413**	0.387**	0.406**	0.382**	0.468**
Medium	0.028	0.074*	0.384**	0.267**	0.476**	0.365**	0.412**
High	0.167**	0.188**	0.235**	0.152*	0.384**	0.224**	0.481**
Cue Validity	*0.5*	*0.5*	*0.7*	*0.7*	*0.7*	*0.7*	*0.7*

[1] Due to statistical redundancy the investment variable was removed from the models

Table 2 also shows the mean confidence levels reported on each trial by the participants. A repeated measures ANOVA showed that the effect on confidence was significant $F(1.67, 73.24) = 69.88$, $p < .001$. Bonferroni post hoc tests showed that while there was no significant difference between the no time pressure and low time pressure trials in confidence ($p > .05$), all other comparisons were significant ($p < .05$). Thus, it seems that participants were fairly confident in their judgements and only exhibited a shift in confidence when time pressure was high. This decrease in confidence may be representational of the shift towards a perceived greater reliance on type 1 strategies at high pressure.

Table 2. The mean confidence in each decision and pair agreement with the mean time allowed in each level of time pressure.

Time	Mean Time	Pair Agreement			Confidence		
Pressure	(seconds)	N	M	SD	N	M	SD
None	16.72	23	16.87	4.44	46	5.50	0.90
Low	10.03	23	16.00	4.06	46	5.40	0.86
Medium	5.85	23	14.30	4.18	46	5.00	0.91
High	3.34	23	10.87	2.78	46	3.95	1.20

Discussion

Inspired by some of the aspects of default-interventionism, a sequential sample model was used in order to account for the effects of a range of time pressures on type 1 and type 2 processing. Consistent with model and the simulations in Chapter III, when the type 1 and type 2 cues were incongruent, accuracy was lower than when they were congruent. Importantly, this congruency effect was greatest at high time pressure, an effect also predicted by the model. Furthermore, the R^2 values (coefficient of determination) for the sequential sample model predictions for the choice data revealed a reasonably effective fit of about .28 for both congruent and incongruent trials. The findings suggest that this sequential sample modelling approach has some future potential for capturing the general relationship between type 1 and type 2 processing over a range of time pressures. These findings contribute to past studies into the effects of time pressure on strategy usage (Ben-Zur, & Breznitz, 1981; Wallsten, 1993; Payne, Bettman, & Johnson, 1988). The increased use of experiential processing under high time pressure is consistent with past studies into motivated reasoning (Freund et al., 1985; Kruglanski & Freund, 1983; Kunda, 1990).

A limitation of the sequential sample model is that it failed to account for the increased use of type 1 processing in no time pressure compared to low time pressure conditions. This is an important limitation of the sequential sample model which, as discussed in the Chapters III and IV, is a simplified representation of *some* of the dual-process literature. Therefore, the failures of this model do not necessarily reflect weakness in dual-process theory, but rather more likely, failures in the quantitative model to capture the nuances of dual-process theory as a whole. In particular, in the sequential sample model, its structure means that type 1 processing can always be overridden by type 2 processing given an infinitely high threshold. However, the degree of volitional control in overriding type 1 processing does depend on the task. For example, Evans, Handley and Bacon (2009) revealed that instructions designed to inhibit the belief bias effect failed to remove the bias in conditional inference. Furthermore, in contrast to findings that time pressure increased belief bias in a syllogistic reasoning task (Evans & Curtis-Holmes, 2005), this increase in belief bias did not occur in a conditional inference task. Therefore, it is not true to say that intervention from type 2 processing can always remove the effects from default type 1 processing as is implied by the sequential sample model shown in Chapter III. Indeed, type 2 processing often relies on type 1 processing for some tasks. For example, as discussed in Chapter I and II, the correct assessment of risk information has been shown to rely on emotional (type 1) processes (Shiv, Loewenstein, Bechara, Damasio, & Damasio, 2005; Berthoz, 2006; Damasio, 1994; Bechara, Damasio, Tranel & Damasio, 1997). This limitation will be returned to in Chapter VII.

A further question which remains as a result of this study is the extent to which these results are due to within participants effects (i.e. a weighted input from both systems into each choice), or across participants effects (i.e. time pressure increases the likelihood that participants will switch to an entirely experiential strategy). The model and the methodology were aimed at determining whether there is a global increase in type 1 cue usage overall and could not discriminate between these different levels of causation. Another important limitation is that this study does not involve competitive modelling analysis, e.g. comparing two models to determine which one is the best predictor. Rather this study simply assessed the ability of the model to account for the shape of the data. Competitive assessment of the model is considered in the next chapter.

In conclusion, while a more complex version of the sequential sample model would be required if we are to capture more of the nuanced effects relating to dual processes, the results shown that even in its very simplistic form, it can perform relatively well at accounting choice behaviour over a range of time pressures. In chapter VII I consider the various limitations of the sequential sample model, and outline how it may be improved to better capture other aspects of dual-process theory and reflect the broader JDM literature.

Summary Points

- Under default-interventionism, type 3 processing is hypothesized to mediate the extent to which individual rely on the default, type 1, processing or allow more time consuming type 2 intervention to occur.
- The simulations in Chapter III predict that greater time pressure should result in greater reliance on type 1 processing.

- While increased use of type 1 processing under time pressure is represented in the literature, the experiment in this chapter tested the extent to which the model's predictions over a range of time pressures (continuous predictions) reflected the behavioural data.
- The experiment revealed that the predicted choice behaviour did reflect the general changes in empirical data over the four levels of time pressure.
- However, while the general patterns of behaviour could be represented by the model, the model failed to account for the use of type 1 processing in no time-pressure compared to low time-pressure condition. As such behaviour could be explained via dual-processes, this demonstrates a further limitation based on the simplicity of the mode which needs to be addressed in Chapter VII.
- Furthermore, while the sequential sample model can account for congruency effects, it is unclear as to whether it is a better model than the alternative, race model, approach. Competitive modelling would improve the case for the sequential sample model mechanism outlined in Chapter III.

Chapter VI – Empirical Chapter

"We don't see things as *they* are, we see things as *we* are."
- A. Nin (*1903 - 1977)*

In the previous chapter, I focused on the congruency effect of type 1 and type 2 processing under various levels of time pressure. This chapter continues the investigation of the congruency effect but this time also examining whether the specific mechanism used to predict these effects (sequential sample / tug of war) mechanism is a more effective predictor than an alternative mechanism (race model) (see discussion in Chapter III). Thus, while the previous chapter only tackled the descriptive validity of the model, i.e. the extent to which the model estimated behaviour appeared to reflect the shape of the empirical data, this chapter seeks a more competitive modelling approach. Therefore, this chapter seeks a more rigorous assessment of the model mechanism as a valid representation of JDM processes. As discussed in Chapter III, the race model only allows early information to reduce the distance to the congruent threshold (congruency effect). The race model does not allow early-informational biases to impact to impact negatively on the opposite threshold (i.e. no incongruency effect is predicted). The sequential sample model, on the other hand, makes a bolder prediction that not only does a type 1 bias reduce the distance to the congruent threshold, it will also extend the distance to the negative threshold (i.e. it predicts both a congruency and incongruency effect). These competing predictions are tested in this Chapter. The null hypothesis is that we should not observe an effect of a type 1 bias on the distance to the opposite decision threshold (race model prediction). If I do find a significant effect on the opposite threshold then we can reject this null hypothesis (and the race model mechanism) in favour of the sequential sample model mechanism described in Chapter III.

In addition to testing this question of congruency/incongruency effects, the previous study focused on the effect of reducing decision thresholds through time pressure. This study is complementary, therefore, as it focuses on manipulations of type 3 processing in the opposite direction – the effect of an increased satisficing threshold level through motivation manipulation. In particular, I explore the role of motivated accuracy on the congruency/incongruency effect and the extent to which the sequential sample model correctly predicts empirical data. The model makes two predictions related to motivated accuracy. The first is that type 1 biases should have a reduced effect. The second is that motivation to be accurate should impact on type 3 processing and therefore we should observe this in the volume of evidence required before a decision is made (i.e. increased deliberation times/RTs). Thus, this study also continues the work of Chapter IV on the use of response times as evidence of type 3 processing.

Bounded Visual Search: Expectation Biases and Motivated Accuracy on Visual Search Performance

Abstract

Participants performed a visual search "war game" in which participants had to decide whether to state that an enemy threat was present or absent in a display of distracters. Continuing the theme of early informational biases and the role of type 3 processing in mediating the biasing effects, this study examines the role of accuracy motivation (theorised to impact on type 3 processing) and cues eliciting expectation (an early informational bias) regarding search outcome on individuals' judgements. Prior to each trial, participants were shown a threat-level cue designed to elicit an expectation regarding the likelihood of target presence; either present, absent, or neutral (non-informative). The results of the first experiment showed that the valence of the expectation resulted in an interaction between miss errors and false alarms, as well as influencing hit response times and the decision to stop searching. This persisted whether or not the cue was a valid indicator of actual target presence. In a second experiment a payoff for accuracy was introduced. This motivation removed the effect of the cue on error rates whilst generally increasing RT; an accuracy-speed trade off. More importantly, however, whilst the effects on error rates were removed, the interaction in the RTs was still observed. This finding supports the outweighing mechanism used in the sequential sample model, rather than a system which takes type 1 responses totally "offline". Critically, the demonstration of an incongruency effect demonstrates support for the sequential sample mechanism, rather than the race model mechanism which would not predict any incongruency effect.

Introduction

In the real world the act of visual search seldom occurs in a vacuum devoid of cognitive factors such as emotion, expectation and motivation. Consider a visual searcher who expects a target to be present; an x-ray image of a patient previously diagnosed with cancer, a "Where's Wally?[9]" game, a key in the place we last recall leaving it, a ridge characteristic from a forensic fingerprint from the prime suspect. Now consider a search in which it is fairly certain that a target is not present; a medical image of a healthy patient, a baggage x-ray image at an airport owned by an elderly lady, or a ridge characteristic from a forensic print taken from an unlikely suspect. Would the search effort (type 3 processing) always be the same across these contexts? These cognitive factors are rarely considered in

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[9] Called "Where's Waldo?" in the United States.

visual search research beyond finding ways to control them out through experimental design. Therefore it is unclear as to how these higher-level cognitive processes can impact on visual search performance. Accordingly, I consider whether the sequential sample approach introduced in Chapter III may be a useful tool for predicting these kinds of factors in the domain of visual search decision-making.

Expectation as Type 1 Priming of Responses

There are a number of expectations we might have concerning a forthcoming search, the effects of which would fall under the category of automatic processes. Priming usually refers to some process which elicits increases in target saliency (Egeth, 1977; Julesz, 1986; Moraglia, 1989) or guides attention (Wolfe, Butcher, Lee, & Hyle, 2003), either due to the stimuli themselves, having learnt task specific cues, or having been informed of some knowledge concerning the search task. Posner and Snyder (1975) describe the effects of priming on stimulus response tasks. In their experiment it was found that cues presented before a stimulus-response task decreased response times (RTs) even when the cues were of low validity (the cue was correct only 20% of the time). This showed that repeated pairing of the cue and the stimulus resulted in priming without any expectation (Reisberg, 1997). It was also found that when the cues were of high validity (the cue was predictive 80% of the time), the RTs were even faster than the low validity trials. Posner and Snyder also provided misleading cues. These cues were not neutral but indicated that a different stimulus would appear. The effects of the misleading cues were negligible when compared to neutral cues under low validity trials. This suggested that priming the “wrong” response did not always negatively impose on RTs, i.e. the priming of one type of stimulus did not appear to influence the sensitivity to others. However, during high validity trials, the misleading cues significantly increased the RTs. It was suggested that the high validity cue also brought about a certain level of expectation and hence explicit aspects onto the perceptual task. It seemed that this explicit priming of one response appeared to take away some sensitivity towards the alterative response (Reisberg, 1997). This suggests that an expectation that a target is going to be present or absent in a search area may affect our response sensitivity in a way which biases response probability towards one judgement over the other.

If one considers this initial expectation of target presence/absence as a type 1 processing bias on subsequent searching, then the reduction in response sensitivity to the opposite response is in line with the congruency/incongruency effects predicted by the sequential sample model outlined in Chapter III. The question, therefore, is whether this initial expectation of target presence/absence impacts on choice behaviour in line with other predictions of type 1 biases described by the model. For example, does a manipulated increase in satisficing threshold, which should reduce the impact of the type 1 response, reduce the impact of a cue eliciting the expectation of target presence/absence?

Although the focus is on the effect of expectation of target presence, it may be useful to briefly describe studies examining implicit priming of target presence; the *target prevalence effect*. This is an effect on search performance as a result of experiencing certain levels of target prevalence over many trials. Wolfe, Horowitz, and Kenner (2005) found that a target presented on 1% of trials was less likely to be detected than a target presented on 50% of trials. In addition, Wolfe et al. (2005) observed that RTs for target-absent trials became more rapid as target prevalence was reduced. This was attributed to a speed-accuracy trade-off, with RTs in low prevalence search becoming so rapid for target-absent responses that the observer is essentially responding before they have allowed themselves a sufficient period of time to detect the target (Chun & Wolfe, 1996).

The detailed nuances of the prevalence effect are still under examination (see Wolfe, Horowitz, Van Wert, Kenner, Place, & Kibbi, 2007; for review). However, it does appear that the effect is intricately tied to RTs. It is possible that the RTs are a result of some internally-limiting process which results in observers responding “absent” more rapidly, but, for the time being, it is uncertain why this is the case (Wolfe et al., 2007). However, in terms of the simulations in Chapter III, this phenomenon appears to be in line with a reduction in the distance to the congruent threshold and type 3 processing.

Thresholds in Decision-Making and Visual Search

In visual search, an important topic of interest is the decision to stop searching and make a present/absent decision. This topic has close parallels to type 3 processing discussed throughout this thesis and the idea of satisficing thresholds. One of the most thorough examinations of the decision to stop searching was Chun and Wolfe’s (1996) solution based upon Wolfe’s (1989, 1994, 2007) Guided Search model. Their theory states that searchers will check as many target-like stimuli as exceed a threshold. By “threshold”, the mean that the stimuli appear to be relevant/similar to the search target. This is different from the satisficing threshold I describe in Chapter III. Once all the targets which meet this criterion have been checked, and a target is not found, then searching stops. Accordingly, searching does not have to be exhaustive, i.e. searching all items in the visual scene, but can vary depending upon the level set by the criterion.

Chun and Wolfe (1996) then considered that there may be effects of motivational factors such as cost of error on this stop-search mechanism. This was tested through two groups of participants, one in which the cost of error on their overall score was large, and one in which it was small. The “conservative” group had a higher cost of error than the “liberal” group and were shown to have similar RTs for target trials but higher RTs during blank trials. Furthermore, miss error rates for the liberal group were 2.5 times greater than in the conservative group and false-alarm rates, although to a lesser extent, were also increased. Although it was not discussed by Chun and Wolfe, the idea of type 3 processing and motivational factors on search performance clearly echos the studies of motivation on decision processes and the rich literature relating to thinking dispositions (Cacioppo, Petty, Feinstein, & Jarvis, 1996).

Accordingly, the sequential sample model approach I considered may be useful for understanding these effects. In fact, sequential sample models have been used in visual search. Ward and McClelland (1989) were among the first to relate a sequential sample model (termed a diffusion model) to visual search, using a parallel search paradigm. They proposed that each item in a display has a corresponding detector, all of which accumulate evidence for or against the hypothesis that their item is a target. Each detector has a resting activation, similar to the type 1 bias parameter z, and a “present” and “absent” threshold. If a single detector reaches the positive threshold, then a “present” decision is made; once all items reach the negative threshold, an “absent” decision is made. Thus, in a similar way to Chun and Wolfe’s (1996) idea, modulation of these thresholds determines RTs and accuracy rates.

The main difference is that whereas the Chun and Wolfe’s model varies the number of target-like items examined, Ward & McClelland’s model varies the number of samples of visual information that are required for each item before it is said to be a target or a distracter. I shall return to this difference in the discussion, nevertheless, both models use a threshold to represent a speed-accuracy trade off. Given a low threshold, less visual evidence is required before a verdict is made resulting in quicker RTs but increased error rates. Given a desire to make a more accurate decision, the thresholds will increase resulting in slower RTs but more accurate searches as judgements are made using more samples of information. Chun and Wolfe (1996) and the many theories of bounded rationality and motivated reasoning suggest that motivational factors may influence this decision threshold. Therefore, grounded in these theories is a single parameter (mean detector threshold level, θ) which can represent the motivation to either perform a long, accurate search or a short, more error-prone search. Figure 1 shows a depiction of the effects of a shift in thresholds on RTs showing how the increase in threshold from θ_1 to θ_2 results in a global increase in the number of samples required for judgement. This increase in the volume of evidence gathered will reduce error rates in both target present and target absent trials, resulting in an speed-accuracy tradeoff.

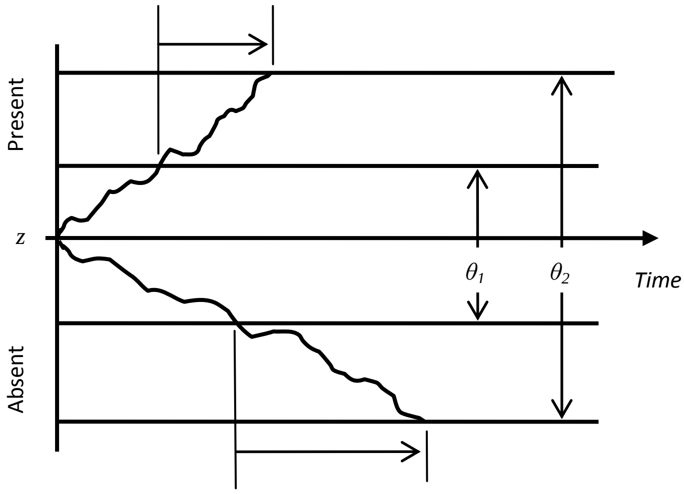
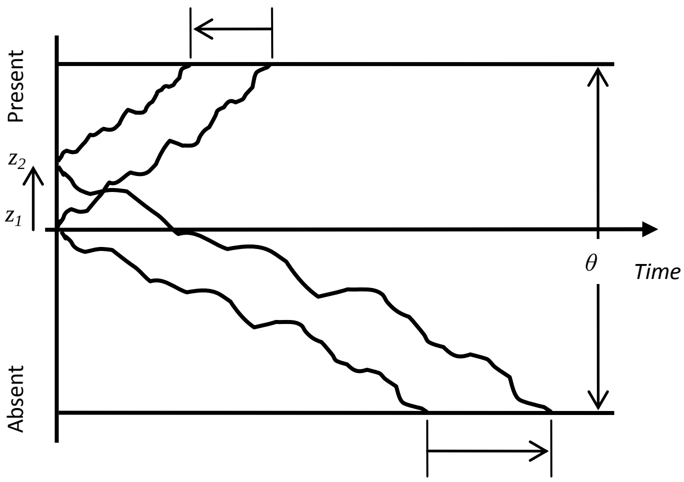


Figure 1. A representation of the effects of thresholds on evidence gathering and accuracy-speed tradeoffs, an effect of accuracy motivation.

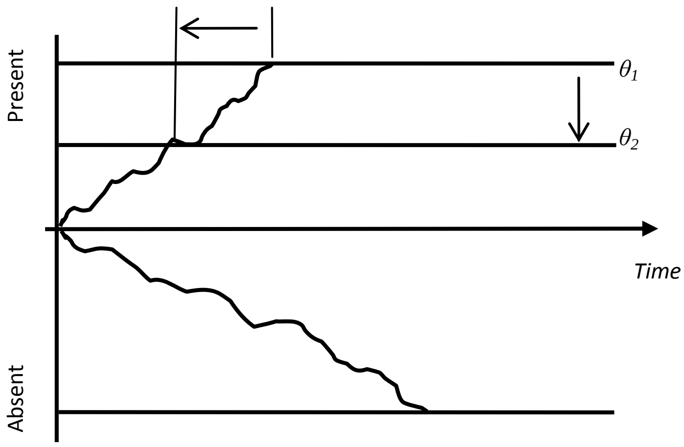
Expectations and resting activations: Sequential Sample versus Race Model Mechanism

Whilst the speed-accuracy tradeoff aspect of the model may be useful for the effects of accuracy motivation, an initial expectation of target presence/absence may also relate to performance, acting as a type 1 processing bias. The sequential sample model introduced in Chapter III proposes that the bias towards one hypothesis (e.g. present conclusion) may negatively impact on the distance to the opposite threshold (e.g. absent conclusion). See simulations 4 and 5 in Chapter III and Figure 2a. However, an alternative possibility is that expectation may not influence the resting activations. Rather, the threshold distances may vary independently of each other - a form of race model (see Chapter III). This would be displayed by positive effects on the congruent response but no effect on the incongruent response performance (see Ratcliff & Smith, 2004, for review). This study can help determine which model is the best predictor of expectation on search performance.

In summary, this study aims to examine whether the sequential sample model can predict the role of early information regarding target presence/absence under motivated and unmotivated conditions. In particular, I focus on the predicted incongruency effect which is predicated by the sequential sample model but not by race model mechanism. The study will focus on both accuracy and also RTs providing indications of the effects of type 3 processing.



(a)



(b)

Figure 2. (a) A sequential sample model of expectation bias: the effects of a shift in resting activations, z_1 to z_2, on the evidence required for each response; an effect of expectation of target presence (congruency effect for the present decision but incongruency effect for the absent decision). (b) A race model of expectation bias: the shift from θ_1 to θ_2 only affects the congruent outcome and does not impact on the opposite (absent in this case) threshold.

Experiment 1

Expectation Cue as a Type 1 (z) Bias

This first study examines whether providing a cue prior to a search trial will result in behaviour predicted by the sequential sample model. According to the simulations in Chapter III, a cue eliciting an expectation that the target is present should result in a shift in the initial preference state (P(0), z) towards the "present" threshold. With this we should observe faster hit RTs (predicted by both the sequential sample and race model mechanism).

However, if we observed longer correct rejection RTs then we have evidence in favour of the sequential sample model but not the race model. This will be associated with reduced miss rates (target present trial (TPT) errors) but increased false alarm rates (target absent trial (TAT) errors).

Participants performed a visual search task searching for a specific single target amongst distracters. Prior to each trial, participants were presented with a cue designed to elicit an expectation concerning target presence. If a decision-maker is aware that a cue has little or no validity (i.e. it is unhelpful), then they may tend to ignore it and the resting activations may not be influenced. Therefore, two groups were tested: one group had cues of high validity (the cue is predictive of target presence), another group had low validity cues (the cue is predictive of target presence in only 50% of trials). Unfortunately, this has a potential to make analysis difficult. If only the valid cue group reveal an effect, it may be difficult to determine whether the effects are a result of the cues or the bottom-up effects of the actual prevalence of the target (see section on the target prevalence effect above). The invalid group isolates the effects of the cue but this may lead to no effect of the cue as participants may fail to believe the cue to be useful. Therefore, a solution is to use a mixed-block design to limit the target-prevalence effect; i.e. all cues are presented within each block rather than between blocks. This should reduce the likelihood that the target prevalence effect will confound results in the valid group, whilst at the same time making it more difficult for searchers to determine the actual validities in the invalid group.

Method

Participants

Thirty-two participants were recruited, aged between 18 and 43 (*M*=22.0, *SD*=6.0). There were 20 female and 12 male participants in the group and they were all students at the University of Southampton. Participants were rewarded with class credits.

Design

There were two independent variables. The first was the expectation cue presented prior to each trial which was varied within participants and had three levels: Expect Present, Neutral or Expect Absent. The second was whether the target presence across trials meant that the cues had high validity or not. The high validity group experienced target prevalence which agreed with the expectation cue; i.e., in expect-present trials the target was present 70% of the time, in neutral trials 50% of the time, and in expect-absent trials 30% of the time. The low validity group had 50% present and 50% absent trials across all trials. The design was a mixed block design in that a different cue may be provided in each trial in a random order. This means that it is possible to isolate the effects of top-down priming as without the cue prior to the trial, even in the valid group, the experienced target presence would be 50% across all blocks, see (Table 1). Response times, and whether the searchers chose to press the “present” or “absent” response button, were analysed. Note that although we have referred to the groups as high and low validity, the 50% trials are in fact valid for both. Hence, the 50% trials act as a control, or measure of consistency between groups, and aid our ability to isolate the real effects of validity on choices.

Stimuli and Procedure

Participants were undergraduate students at the University of Southampton rewarded with course credits. The experiment was carried out in an experimental laboratory. They were given an information and consent form prior to each task (see appendix A for an example) and were fully debriefed after the experiment. Participants took part in a visual search game, searching for a specific schematic of an airplane target amongst an array of distracters. The stimuli consisted of JPEG images taken from hand drawn schematics which were manipulated using photo editing software to ensure they each had similar levels of luminance and line thickness. Each image could be displayed in four different orientations, with the nose of each plane pointing either at the 0, 90, 180, or 270 degrees of orientation. Each trial had a set size of 12 images, with three images displayed in each of four orientations. The target was randomly assigned to each orientation across trials. Despite the planes being different sizes in real life, each image was the same dimensions: height 176 by width 184 pixels, to eliminate any size-based pop-out.

A bank of target planes was chosen by excluding planes which appeared to stand out from the rest in a short pre-study. Out of a bank of 55 images, 20 potential targets were selected based on similarity of image, number of engines and wing design. Then a group of five participants were asked to identify any image which appeared to stand out as particularly different in design to the others. The four most outstanding planes were kept as distracters but removed from the potential target list. Thus there were two banks: a target bank of 16 planes and a distracter bank of 39 planes. Each participant was asked to search for the same single target throughout the experiment and the target was counterbalanced across the 32 participants. To attempt to ensure consistency of complexity across trials, seven distracters were from the distracter bank and five were from the target bank (excluding the target).

Table 1. Total number of trials for the high and low validity group.

Validity		Expect Absent	Neutral	Expect Present	*Total*
	Absent	640	224	256	1120
High	Present	256	224	640	1120
	Total	896	448	896	2240
	Absent	448	224	448	1120
Low	Present	448	224	448	1120
	Total	896	448[10]	896	2240

Participants were informed that they were playing a game where they had to protect the City of London by identifying a specific enemy airplane target which may or may not be present. In each trial, participants were shown a reminder of the target image in the 0 degree orientation for 4000ms. They were then shown the expectation cue. This was a threat level for the forthcoming trial which was either: “expect present” (a red image stating “High Threat Level” linked with an alarm sound cue), “neutral” (a blue image stating “Medium Threat Level” with a soft tone sound cue), or “expect absent” (a green image stating “Low Threat Level” with a small bell sound cue). The high threat level was said to be associated with over 70% present trials, the medium threat level was said to be associated with 50% present trials, the low threat level was said to be associated with over 70% absent trials. Participants then pressed the space bar when they were ready to begin, whereupon the screen displayed the stimulus. This remained visible until the participant responded by either pressing the “N” keyboard button for present or “V” keyboard button for absent. After 30 practice trials both groups were presented with four blocks of 42 trials. Table 1 displays the trial distributions for each group depending upon the cue presented prior to each trial.

Results

Table 2 shows the descriptive statistics for error rates by both groups. Figure 3 shows the error rates in target present and target absent trials across both groups depending upon the cue presented before each trial. The results showed a significant interaction

[10] There were originally 896 neutral trials, however, there was a data error in blocks 3 & 4 for this trial type and so these data were not recorded.

between the cue and the type of error, $F(1.26, 37.87$[11]$) = 5.51$, $p < .05$. This interaction was not affected by the validity groups, $F(1.26, 37.87) = .637$, $p > .05$.

Table 2. Descriptive statistics for the high and low validity groups for error rates.

		Misses			False Alarms		
Validity		Exp Absent	Neutral	Exp Present	Exp Absent	Neutral	Exp Present
High	M	.213	.170	.093	.048	.158	.144
	SE	.059	.045	.023	.021	.050	.069
Low	M	.204	.200	.080	.079	.100	.172
	SE	.059	.045	.023	.021	.050	.069

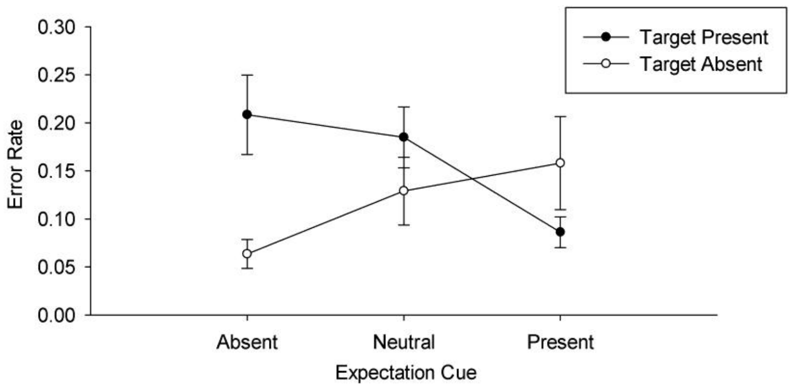


Figure 3. Error rates during target present trials (TPTs) and target absent trials (TATs) from both groups.

The interaction revealed that different types of error were being made depending upon the cue valence. There was an effect of cue on the false alarm rates, i.e. in target absent trials, $F(1.33, 39.90) = 4.10$, $p < .05$. The test for contrasts between cues found a positive linear relationship between cue and false alarm rates, $F(1, 30) = 4.64$, $p < .05$, Bonferroni post-hoc tests could not reveal a significant difference between the individual cues ($p>.05$ for all). Notably, although greater expectation of target presence resulted in increased false alarm rates, this also led to a decrease in misses, $F(1.52, 45.73) = 5.97$, $p < .01$. The test for

[11] In cases in which it was necessary, due to significant Mauchly's tests, the degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity. In the other cases the original degrees of freedom were used.

contrasts between cues found a negative linear relationship, $F(1, 30) = 9.316$, $p < .01$, and Bonferroni post hoc tests revealed a significant difference between the expect-present and expect-absent cues ($p < .05$), the expect-present and neutral cues ($p < .01$), but not between the neutral and expect-absent cues ($p > .05$).

In terms of signal detection theory (Table 3), there was no significant effect of the cues presented to participants on d-prime, $F(1.54, 46.09) = 2.44$, $p > .05$. Equally, there were no differences between the validity groups on effect of cues on d-prime, $F(1.54, 46.09) = .42$, $p > .05$. This indicates that there was no effect of the cues or difference between the groups on the ability to detect a target or not. However, there was a significant effect of cue on the response criterion, $F(1.47, 43.98) = 6.11$, $p < .01$. This indicates a bias towards one decision over another. Again, there was no difference between groups on this response bias, $F(1.47, 43.98) = 2.40$, $p > .05$, or an interaction between validity group and cue, $F(1.47, 43.98)=1.32$, $p>.05$. Bonferroni post hoc tests revealed a significant difference between expect-present and expect absent cues ($p < .05$) however, the neutral cue was not significantly different from either of the other two cues ($p > .05$).

Table 3. Mean (SE) signal detection theory values for each validity group under each cue.

	d-prime			criterion		
	Present	Neutral	Absent	Present	Neutral	Absent
High Validity	3.328 (.425)	2.916 (.437)	3.175 (.352)	.054 (.226)	-.044 (.206)	.588 (.148)
Low Validity	3.426 (.425)	3.006 (.437)	2.957 (.352)	-.159 (.226)	.361 (.206)	.407 (.148)

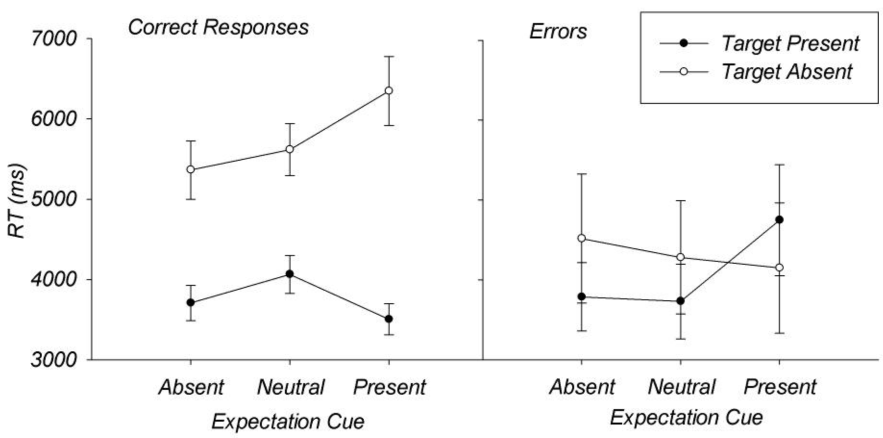


Figure 4. Response Time data for correct and incorrect responses during target present trials (TPTs) and target absent trials (TATs).

Figure 4 shows the RT data from the study for both correct and incorrect responses under the different cues for both target present and target absent trials. The results for the correct responses revealed an interaction between correct rejection (TATs) and hit (TPTs) RTs, $F(1.36, 39.34) = 11.43$, $p < .001$, which was not significantly different between the two validity groups. As may be expected, overall, hit RTs were quicker than correct rejection RTs, $F(1, 29) = 95.44$, $p < .001$, and there was an effect of cue on hit RTs, $F(2, 60) = 5.44$, $p < .01$, which was not significantly different between the two validity groups, $F(2, 60) = 1.93$, $p > .05$. Bonferroni post hoc tests revealed that hit RTs were quicker after the expect-present cue than the neutral cue ($p < .001$); no other comparisons were significant, ($p > .05$). There was also an effect of cue on correct rejection RTs, $F(1.21, 35.15) = 11.19$, $p < .001$, which was not significantly different between validity groups, $F(1.21, 35.15) = .70$, $p > .05$. This effect was linearly related to cue valence, $F(1, 29) = 11.50$, $p < .01$, and Bonferroni post hoc tests revealed that correct rejection RTs were slower after the expect-present cue than both the neutral cue ($p < .001$) and the expect-absent cue ($p < .01$). There was no significant difference between the correct rejection RTs between the neutral and the expect-absent cue ($p > .05$)[12].

These results appear to show that, consistent with the sequential sample model predictions, searchers are quicker to correctly identify the target when they expect that the target will be present and the signal detection theory results clearly show this to be a response bias effect. Importantly, consistent with both the sequential sample theory predictions and Posner and Snyder's (1975) findings, correct rejection RTs increase as expectation of target presence increases. This suggests that the decision to stop searching does indeed vary depending on the expectation of target presence. As predicted by the sequential sample model, but not the race model, this bias towards the "present" threshold also results in a bias away from the "absent" threshold resulting in more evidence being required before the absent threshold is reached by the accumulation, increasing RTs. Essentially, the results showed that an expectation influenced both the expected outcome threshold distance (shortened) as well as the opposite hypothesis threshold distance (lengthened). This significant effect shows that the sequential sample model, rather than race model, mechanism was correct.

As we did not observe any effect of cue validity on this effect, it appears as though participants were not aware of the validities of the cues in each case. Indeed, the fact that the effects of the cues on error rates were found after the first block with an interaction between

[12] As the error rates were relatively small, we have only limited number of data points for false alarm and miss rates and so we did not find any significant effects in this data set.

misses and false alarms depending upon the cue, $F(1.65, 51.21) = 7.862$, $p < .01$, suggests that validity was believed from the outset. This shows that experience of validity is not necessarily required for biases in resting activation to occur; a cue which is believed to be valid is enough. This clearly shows higher level processes in the bias rather than some degree of stimulus-response learning based on feedback.

Experiment 2

Thresholds (θ) × Resting Activations (z)

Given that expectation influences searching in a way which is consistent with the sequential sample model approach, it is possible to make further predictions concerning these effects and type 3 processing. In the last experiment, participants were given no reward or motivational cues other than to respond as accurately and quickly as possible. However, Chun & Wolfe (1996) discovered that payoffs resulted in significant effects on both target absent trials RTs as well as error rates. According to their theory this motivation mediated the threshold and thus determined the level of speed-accuracy trade off. As a result, there may be an interaction between the resting activations and the threshold levels. Based on the theory that motivated accuracy may impact on type 3 processing, i.e. satisficing thresholds, it is predicted that the sequential sample model may also be useful in predicting these effects.

The general relationship between early type 1 biases and satisficing thresholds, predicted by the sequential sample model, is that a bias in resting activation has a greater effect when the thresholds are low than when they are high (see the simulations in Chapter III). Accordingly, if motivation increases the satisficing threshold, then the bias will have a reduced effect. The sequential sample model predicts a reduction in the magnitude of the congruence/incongruency effect on both accuracy and RTs.

Method

Participants

Thirty-two participants were recruited, aged between 19 and 43 (M=24.5, SD=7.5). There were 19 female and 13 male participants in the group and they were all students at the University of Southampton, rewarded with class credits.

Design

As we observed no significant difference between the valid and invalid cues, and the invalid design allows for more misleading cue trials for analysis, this study replicated the invalid condition, i.e. in every expectation cue condition the target appeared 50% of the time. Again, note that the neutral cue is valid as it has been before and thus acts as the control. Under this design we can be sure that the effects are wholly due to the cue and implicit effects of experiencing variation in actual target prevalence are removed and are not affected by experiencing different prevalence rates. One group were not given any payoff for accuracy (non-motivated); the second group were informed that they would be financially rewarded depending upon their accuracy (motivated).

Procedure

Participants were undergraduate students at the University of Southampton rewarded with course credits. They were given an information and consent form prior to each task (see appendix A for an example) and were fully debriefed after the experiment. The experiment was carried out in an experimental laboratory. The motivated participants were rewarded with £5 if they had a low enough error rate (both misses and false alarms below 98%), and the participant who had the least errors overall would receive £50. In the event of a tie, the participant with the fastest overall RT out of the competitors would win. The rest of the procedure and design were identical to the last study.

Results

Figure 5 shows the error rates of motivated and unmotivated participants. The non-motivated group showed an almost significant effect of cue on error rates which interacted across target present and target absent trials, $F(1.18,17.62) = 3.38$, $p = .078$. There was an effect of cue on miss rates, $F(2,30) = 3.29$, $p = .05$, and Bonferroni post hoc tests revealed that non-motivated searchers were less likely to miss the target when they expected it to be present, $p < .05$. No other comparisons were significant. In contrast, motivated participants made fewer errors overall when compared to the non-motivated group, $F(1,29) = 6.91$, $p < .05$. This decrease was found in both target present trials (misses) $F(1,30) = 6.47$, $p < .05$, and target absent trials (false alarms) $F(1,30) = 6.59$, $p < .05$. While motivated participants still made more miss errors than false alarm errors, $F(1,15) = 14.23$, $p < .01$, there was now no effect of cue on error rates $F(1.46,20.43) = .959$, $p > .05$.

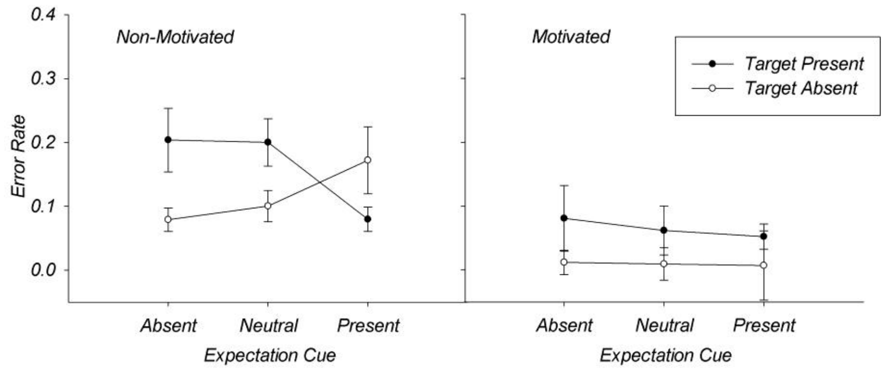


Figure 5. Error rates for both the motivated and non-motivated groups.

Signal detection theory results (Table 4) show that there was no difference between the groups in d-prime $F(1,30) = 1.84$, $p > .05$, and no effect of cue on d-prime for either the non-motivated $F(2,30) = 1.57$, $p > .05$, or the motivated group, $F(2,30) = .88$, $p > .05$. There was no effect of cue on d-prime overall (i.e. across both groups), $F(2,60)=2.123$, $p>.05$, or an interaction between groups and cue, $F(2,60)=.776$, $p>.05$. There was a significant interaction between groups and cue in criterion estimates, $F(1.64,49.07) = 4.752$, $p<.05$. It was revealed that while there was an effect of the cue on SDT criterion estimates in the non-motivated group, $F(2,30) = 4.83$, $p < .05$, this effect was not present in the motivated group, $F(2,30) = .29$, $p > .05$. This suggests that the cue only significantly influenced response biases when participants did not have heightened motivation levels. This effect in the non-motivated group was linear $F(1,15) = 5.24$, $p < .05$, such that a cue eliciting an expectation of presence led to a negative bias (more false alarms than misses) whereas neutral or absent expectations led to a positive bias (more misses than false alarms).

Table 4. Mean (SE) signal detection theory values for each motivation group under each cue.

	d-prime			criterion		
	Present	Neutral	Absent	Present	Neutral	Absent
Non-Motivated	3.426	3.006	2.957	-.159	.361	.407
	(.328)	(.332)	(.293)	(.144)	(.091)	(.109)
Motivated	3.757	3.716	3.585	.164	.168	.215
	(.328)	(.332)	(.293)	(.144)	(.091)	(.109)

As discussed, the sequential sample approach predicts that RTs should increase with accuracy motivation as more samples are required to meet the thresholds. The results (see

Figure 6) showed that there was a significant effect of motivation on correct response RTs[13], $F(1,30) = 4.687$, $p < .05$, such that motivated participants took significantly longer to respond than non-motivated participants ($p < .05$).

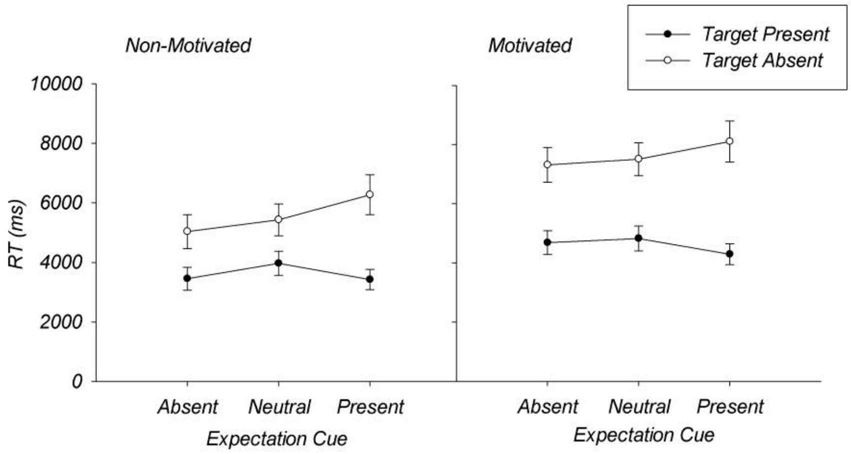


Figure 6. RT data for correct responses in the motivated and non-motivated group.

There was a significant interaction between the cue and correct response RTs in the non-motivated condition, $F(2,30)$, $= 3.749$, $p < .05$. Importantly, although the effects of the cue were removed in the error rates, this interaction persisted even in the motivated group correct response RTs, $F(2, 30)$, $= 10.15$, $p < .001$. There was a significant difference between groups in target absent trial RTs, $F(1,29)$, $= 6.396$, $p < .05$ and correct rejection RTs in the motivated condition were affected by the cue $F(2, 28)$, $= 12.05$, $p < .001$. Bonferroni post hoc tests revealed that, consistent with experiment 1, correct rejection RTs were longer in the high expectation condition than in the medium ($p < .01$) or low ($p < .01$) conditions, although there was no significant difference between low and medium correct rejection RTs ($p > .01$). Thus, an expectation of a target being present again increased the search times in target absent trials. The hit RTs for the target present trials were significantly influenced by the cues $F(2, 30)$, $= 3.36$, $p < .05$. Bonferroni post hoc tests revealed that although this effect was not significant between individual cues ($p > .05$ for all comparisons), there was a significantly linear trend of cue and RT, $F(1, 15)$, $= 4.67$, $p < .05$, such that the greater the expectation of target presence the shorter the RT. The results suggest that motivated participants have not removed their biases by ignoring the cues, but rather the error rate measure is unable to detect the now reduced effects. However, the RT measure is sensitive enough to show that the expectation bias still persisted even in the highly motivated group. These are consistent with the sequential sample models predictions.

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[13] Again, due to the motivated condition there was little RT data from error responses.

Discussion

In two experiments it was shown that a cue presented prior to a visual search task which elicits an expectation of target presence has an effect consistent with the sequential sample model, but not the race model, predictions. Specifically, expectations appear to bias the distance to each alternative's satisficing thresholds so that searchers make confirming responses based upon less visual evidence than they would otherwise (congruency effect), and make disconfirming responses on more information than they would otherwise (incongruency effect). In addition, the hypothesis that motivation manipulations would influence this effect was also tested. The study supports this view by demonstrating that accuracy motivation reduces the overall error rates, as well as the biasing effect of the cues on the types of error made, at the expense of longer RTs. This finding provides further support of the criterion view of type 3 processing and supports the use of satisficing thresholds as a way of modelling at least some of the aspects of this type 3 processing. However, it was also shown that the effect of motivation was not a process of ignoring cues, as the influence on hit and correct rejection RTs persisted even when error rates were no longer affected. Therefore, it is possible to conclude that while expectation still influenced resting activations in motivated searchers, this bias-threshold effect was not high enough for this to significantly influence error rates. Figure 7 shows how motivation mediates the effects of expectation through the resting activation and threshold relationship. This finding supports the outweighing mechanism as opposed to a system which actively takes early biases offline.

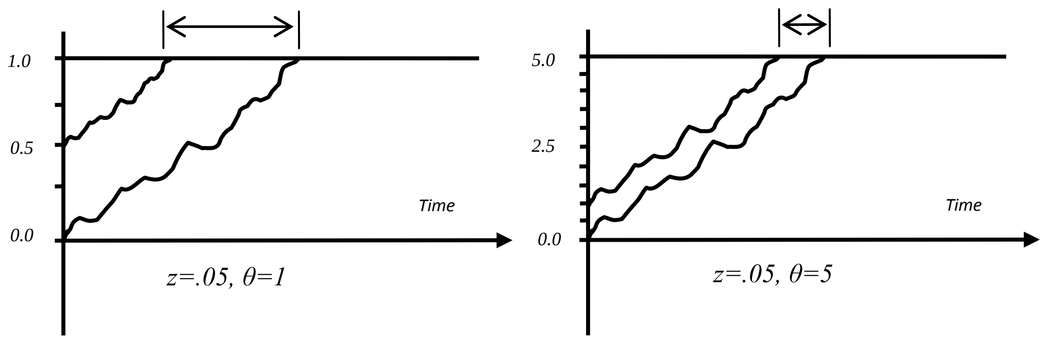

Figure 7. Both figures show a case in which the resting activation is biased towards the "present" threshold, z =.05. This bias is stronger when the threshold is low, θ=1.0, than when it is high, θ=5.0.

Parallel, Serial or Hybrid?

Although the results have been explained using a sequential sample model approach, similar to that of Ward and McClelland's (1989) parallel paradigm, the general process can be applied to other models of visual search (e.g. Humphreys & Müeller, 1993; Pashler, 1987; Grossberg, et al., 1994), all of which appear to need some threshold-based component which can vary our effort between trials (Chun & Wolfe, 1996). These models can be broadly separated into serial (Treisman & Gelade, 1980; Wolfe, 1994) and parallel (Ward & McClelland, 1989; Humphreys & Müeller, 1993) groups. According to serial models, the change in RTs would indicate variations in the number of items examined, and thus misses are the result of searches stopping before the target is observed. However, false alarms are more difficult for these models and can only be accounted for by guessing effects (Chun & Wolfe, 1996). On the other hand, parallel models argue that the changes in RTs represent variation in the number of samples used to judge each item. Thus, misses occur as a target is processed but not marked as a target due to a limited accumulation not meeting the threshold before the absent response threshold. False alarms, on the other hand, occur when target-like stimuli accumulate towards the present threshold (due to their similarity) and this erroneous accumulation is enough to make a choice when the threshold is low enough.

In this study it was impossible to determine whether expectation and motivation influenced the number of items examined (i.e. a serial search effect) or that all items were examined but that fewer samples of each items were taken (i.e. a parallel search effect). Indeed, this question may be impossible to solve as both may be true. Wolfe (2007) describes an asynchronous diffusion model in which both parallel and serial processes can occur simultaneously. The analogy used is that of a car wash, in which a number of items can be washed at the same time but the overall search process is serial. During visual search, the parallel component has a specific capacity, K, thus the K+1 item cannot be examined until one of the items under processing leaves the bottleneck. Yet, even this third hybrid model would predict the same overall findings on RTs and error rates given variations in resting activations and thresholds.

Bounded Visual Search

I take the results of these studies as evidence of the role of type 3 processing in visual search decision-making. These results point towards a bounded view of visual search where contextual cues can influence both response biases and the overall effort that searchers are willing to expend before they make their judgement. Thus, in the same way that Chun and Wolfe (1996) observed that searchers vary their thresholds over time in response to correct and incorrect response, searchers also appear to vary their thresholds depending upon their expectations of target presence and the motivation to be accurate. This may be seen as a dynamic and ongoing attempt to balance search effectiveness and efficiency, i.e. the modulation of satisficing thresholds for different situations. Under low satisficing threshold conditions, the individual relies more on the early, contextual expectation cues, and makes more rapid decisions. Under a high satisficing threshold, the individual relies less on the early, contextual expectation cues, and performs a more thorough but time consuming search. It is important to note that, just as discussed in Chapter V regarding stereotype activation versus application (see Kunda et al., 2002; 2003), in both low and high motivation situations the initial bias is still active.

Future Directions

This chapter examined whether or not the sequential sample model mechanism outlined in Chapter III can effectively predict the role of early contextual cues on visual search performance under different degrees of accuracy motivation. There are a number of future directions. For example, the study did not provide feedback to decision-makers. If this was incorporated then we might observe an effect of feedback on the strength of valid and invalid cues. Indeed, such feedback may entirely remove the effects found in this study. However, in the real world, such consistent feedback is rare, and indeed some real world searchers use biases in their response criteria to account for this lack of feedback. For example, forensic fingerprint examiners deem the cost of a miss as lower than the cost of falsely identifying an innocent individual (false positive), hence they report choosing absent more frequently than present in more difficult prints (Charlton, Fraser-Mackenzie, & Dror, 2010).

This study also examined how searchers vary the volume of information they require prior to choice, yet the volume of information available to them was consistent. Variations in set size (number of distracters in the search) affects the volume of evidence available to searchers and would be expected to affect drift rates (mean travel of preference state across all detectors), and so further studies might examine how all three parameters (drift rate, z biases, and thresholds), interact within this bounded search paradigm and the extent to which it is predictive of behaviour. A further aspect linked to drift rate is the complexity of stimuli; participants were offered complex stimuli (images of airplanes), whereas, in a simple task in which discriminability is quick and easy, the role of expectation and resting activations may be limited unless thresholds are very low (e.g. under time pressure). These variations in drift rates may help account for the phenomenon of asymmetry in search (see Wolfe, 2001). Indeed, the study only manipulated the thresholds in one direction from a non-motivated state level to a higher, motivated, level. Time pressure appears to decrease decision thresholds which would have the potential to increase the effects of biases on error rates (e.g. Dror, Busemeyer, & Basola, 1999, see also Chapter III).

Finally, given that expectation and motivation are both associated with real world search tasks, it might be important to explore the extent to which these factors affect real world searching such as: medical diagnosis, forensic finger-print analysis (e.g. Dror, Charlton, & Peron, 2006), and errors in military identification tasks (e.g. Ashworth, & Dror, 2001; British Army, 2005).

Summary Points

- Given the recent interest into visual search decision-making, on account of its application to important real-world issues, understanding the potential role of early informational biases and type 3 processing seems important.
- Again, I demonstrate that dual-process approaches have much to offer the domain, this time predicting shifts in signal detection parameters based on motivational incentives (acting on type 3 processing) and expectation cues (early-informational biases).
- As the sequential sample model predicts an incongruency effect, whereas the race model does not, experimental design manipulations enabled competitive analysis between the two dynamic modelling approaches. The results were in favour of the predictions made by sequential sample approach and not the race model.
- In addition, again as predicted in the simulations in Chapter III, accuracy motivation (acting on type 3 processing) was shown to limit the effect of these early informational cues on decision outcomes.

Chapter VII – Discussion Chapter

> *"As soon as questions of will, or decision, or reason, or choice of action arise, human science is at a loss."*- (American Philosopher, 1928 -)

Introduction

This thesis began with an interest in the role of early versus late information in JDM. The literature suggested that our initial impressions can play a special role in deliberation. The consideration of type 1 processing in this phenomenon is a fascinating concept but one which I believe is under represented in quantitative models of JDM. For many years researchers focused on the question of whether individuals tend to follow or diverge from normative models (see Stanovich, 2011, and his discussion of the Great Rationality Debate). While this was an important step in our understanding of our capabilities and limitations, many of the prominent JDM models are little more than adaptations from normative models. The adaptations in the models reflect these divergences in JDM behaviour from normative models but nevertheless are still heavily reliant on the normative model primitives. As I discuss in Chapters I and III, this "deconstructive" approach does not result in theories of cognitive process, but rather simply accounts of the degree of divergence from what would be expected if a normative strategy had been undertaken.

I believe that the focus towards these static-quantitative models and towards decision strategies has resulted in a neglect of some important cognitive processes which occur outside of working memory, i.e. type 1 processing (Evans, 2009) and the neglect of some of the more recent proposals such as default-interventionism and type 3 processes. The initial idea employed in Chapter II was to examine how a quantitative JDM model, prospect theory, could be enhanced by considering and dual-process concepts to better account for choices. However, in doing so, I felt that the constraints of using a static-economic model to understand what appears to be a dynamic cognitive process was too limiting would not sufficiently represent the more recent dual-process literature. For this reason, my thesis changed course in Chapter III, taking a more constructive, rather than deconstructive, approach to quantitative modelling and the consideration of dynamic, rather than static, processes via a sequential sample modelling approach.

I also focused on more recent dual-process theory proposals; in particular, the recent consideration of a third type of processing (type 3 processing) and the role of the satisficing principle in relation to the theory of default-interventionism. This third processing system had clear implications for predicting the role of early/type 1 versus late/type 2 processing and I considered the use of decision thresholds as a way of representing some of the aspects of this concept. Importantly, the consideration of this third processing system provided an alternative to the dominant, toolbox, theory of adaptive decision-making and *a priori* strategy selection – a criterion-oriented adaptive decision mechanism.

The Development and Testing of the Sequential Sample Approach

The dynamic-quantitative model was based on sequential sample models and aimed to capture only four characteristics related to default-interventionism: (1) the temporal aspect of deliberation, (2) the default type 1 response (associated with early information), (3) the interventionist type 2 responses (associated with subsequent information), and (4) type 3 processing in the form of a satisficing threshold. While these four characteristics clearly did not reflect all the nuances of dual-process theory, if this highly simplified model could be demonstrated to be useful for JDM purposes, this preliminary investigation could form the basis of the development of a more complex quantitative model based on more features from dual-process theory.

Based on this model, in Chapter III, I produced some simulations predicting certain behavioural outcomes depending on the values inputted into the sequential sample model. There were four main aspects relating to these predictions and the model mechanisms which were tested through empirical studies (see Table 1). Chapter IV focused on aspect 1 and whether the simulated effect of selective exposure to information would indeed result in effects on total evidence volumes and deliberation times (evidence of type 3 processing effects). The focus on evidence volumes and type 3 processing has tended to be neglected in the literature regarding biased predecision processing due to an emphasis on motivational, rather than cognitive process, models. Chapter V focused on aspects 1, 2 and 3, and the predicted response of type 3 processing to four levels of time pressure. This time, however, the experiment assessed whether the predicted relationship between these various levels of time pressure and the congruency of type 1 and type 2 processing on choice behaviour could be captured by the model. The results showed that the model could capture the overall relationship between various levels of time pressure and the congruency effect. Some degree of divergence from model predictions in the no time pressure condition highlighted that a more complex model would be needed to capture all the aspects of dual-process theory; nevertheless, the model demonstrated reasonable R^2. Chapter VI focused on aspects 1, 2, 3, and 4 assessing the predicted response of type 3 processing to motivation manipulation on the congruency effect and also the hypothesised incongruency effect. As the observed incongruency effect would not be expected under an alternative race model mechanism, this study demonstrated further support for the way that the sequential sampled modelled type 1, early-informational, biases.

Table 1. The four aspects relating to the sequential sample model mechanism and the simulation predictions which were assessed in the empirical studies of this thesis from Chapter IV onwards.

Aspect	**Description**
(1) Type 3 Processing Effects	The simulations correctly predicted that we ought to be able to observe the effects of type 3 processing in the volume of evidence gathered as well as in correlated temporal measures (RTs). The model could account for the increased reliance on type 1 information under time-pressure and the decreased reliance on type 1 information under accuracy motivation.
(2) Congruency Effect	The simulations correctly predicted that the congruency of type 1 and type 2 processing should impact on decision accuracy.
(3) Continuous Predictions	The model's prediction of the role of type 1 and type 2 processing over a range of levels of satisficing threshold appeared to match the empirical data with reasonable R-squared values.
(4) Sequential Sample vs. Race Model (incongruency effects)	The sequential sample model outperformed the race model correctly predicting an incongruency effect which would not be expected under a race model.

It should be noted that this thesis covered a wide range of JDM domains and a large number of different experimental tasks. This approach has some clear limitations. In particular, each Chapter is concluded with a number of domain-specific questions left unanswered. I recognize, therefore, that I am unable to provide particularly strong domain-specific comments. Nevertheless, there are some interesting, albeit limited, domain-specific points which can be made based on the experiment outcomes and I cover these first in this chapter. Despite the limitation of undertaking a multiple JDM domain approach, there are some important benefits associated with this approach. Firstly, the fact that a very simple dynamic-quantitative model could be shown to be applicable in numerous different JDM domains indicates the power of these few basic default-interventionist concepts. Secondly, it suggests that these concepts are not domain-specific effects but more fundamental aspects of cognition that may extend even further into other domains. Clearly, this is a result of the decades of work that has gone into dual-process theory but also highlights the opportunity cost associated with the neglect of dual-processes in the JDM domain so far (Evans, 2007a). Therefore, following the domain-specific comments, I shall then discuss the more general implications of the model by looking across the domains and tasks. In particular, I discuss how the dynamic-quantitative approach I employed could be extended further, potential mitigating some of the limitations discovered in the empirical chapters.

Domain-Specific Comments

Bounded Quantitative Judgements: Prospect Theory and Dual-Processes

Chapter II is different from the other empirical chapters because it did not aim to test the sequential sample model introduced in Chapter III. The motivation to develop the sequential sample model, however, stemmed from the consideration of dual-process theory together with a quantitative JDM model – prospect theory. I believe that more can be done with respect to synthesizing dual-processes and static-economic approaches. In particular, I would be interested to examine the place-value heuristic in more detail. Future investigation could assess the factors which act to remove/enhance the use of the place-value heuristic and a greater examination of type 3 processing. A particularly important hypothesis, which should be reasonably straightforward to test, is that increased involvement of type 2 processing should be expected to reduce place-value heuristic assessments. I would be interested to examine the role of accuracy motivation or performance payoffs and this effect and how this might relate to the findings in Chapter VI (where motivation reduced type 1 effects, albeit without removing them entirely). If it was the case then the place-value heuristic could be removed through motivation, then it might even be observed that the normative model would, in fact, better predict choices than the synthesized model in this situation – a complete inversion of the findings in Chapter II. Ultimately, however, the results of my thesis appear to suggest that the synthesized model, traditional prospect theory, and the normative model are simply possible extremes of behaviour that occur depending on type 3 processing.

The technique of using of prospect theory weighting functions as a measurement of dual-process theory effects (experiment 2) also proved useful and could be applied to other dual-process theory effects. It is my opinion that, although prospect theory is a widely accepted model of choice, it does not really explain the cognitive processes which lead to the characteristic functions in the model. Furthermore, it does not indicate when these functions should/should not occur. Indeed as discussed in Chapters I and II this is a problem Kahneman and Tversky themselves admit. The emerging research in neuroscience certainly points to a dual-process account (see Gonzalez, Dana, Koshino, & Just, 2005) and I believe more can be done in this regard. For example, I would like to see whether one could develop a new model which can predict the changes in weighting value functions based on shifts in type 3 processing. For example, can the S-shaped weighting function be fully removed via motivation or, like certain belief-bias effects, is it a persistent bias which can only be mediated to a point. This assessment of the "tolerances" of prospect theory functions would be an exciting step forward.

Bounded Evidence Gathering: Biased Predecision Processing

In Chapter IV, I examined the domain of biased predecision processing. Dual-process theory could explain how and why selective exposure could occur in single novel item evaluation. The experiment demonstrated the value of a cognitive, rather than motivational, explanation for some biased predecision processing effects. I concluded that, despite the neglect in this domain, dual-process concepts ought to be considered as a viable factor in biased predecision process research. In particular, I believe that the notion of the singularity principle (Evans, 2007a) and what Stanovich (2011) refers to as serial associate processing may play an important role in biased predecision processing, a view which stands in contrast to the strong emphasis towards motivational explanations of biased predecision processing. There is clear scope for dual-process theory research in this domain and the general neglect of the theory represents interesting research opportunities.

In particular, it would be interesting to examine the nature of the evidence gathering process in more detail. The sequential sample model approach employed in this thesis was very limited in this regard and was unable to represent much of the dual-process account that I used to explain the types of evidence gathered by participants. However, while the sequential sample model was limited in explaining the types of evidence gathered, it was able to predict the reduction in deliberation times and the number of items read in during selective exposure to information. This was a novel measure in the domain of biased predecision processing and demonstrates how the consideration of type 3 processing can provide new research approaches in some JDM domains.

Based on this chapter, I see scope for the development of a more nuanced dynamic model of biased predecision processing incorporating more of the dual-process literature. For example, in contrast to the motivational literature, the participants did appear to be considering both the evidence in favour of their initial rating as well as the evidence against it. Evans' (2006) heuristic-analytic theory shown in Chapter 1 (Figure 1) has clear implications for biased predecision processing research. Therefore, a quantitative model which could represent the feedback loop of Evans' (2006) heuristic-analytic model (see Figure 1 in Chapter I) combined with being able to predict the volume of evidence gathered over time may prove an exciting new direction for the biased predecision processing domain. A final aspect of the task in Chapter IV was the fact that there were five rating choices (1-5 stars) and yet the sequential sample model I considered only has two outcomes. Thus, there are questions related to how a binary hypothesis model can be extended to better account for multi-alternative decision-making. This important limitation deserves further discussion and is considered in the limitations and future directions section of this chapter.

Bounded Multi-Attribute Decision-Making: Time Pressure and Bias

In the domain of time pressure in JDM, studied in Chapter V, there is considerable emphasis on *a priori* strategy selection and the domineering adaptive decision maker/toolbox framework. The sequential sample model could predict the effect of time pressure on cue usage without *a priori* strategy selection through a default-interventionist approach. Therefore, while the default-interventionist approach to the role of time pressure on type 1 and type 2 processing is not new in other domain such as logic and reasoning research (Evans, Handley, & Bacon, 2009; Evans & Curtis-Holmes, 2005), the application of this approach in a multi-attribute decision task using a quantitative model was novel.

I feel that the neglect to explain precisely how strategies can be effectively selected *a priori* by the adaptive decision-maker framework provides room for alternative conceptualisations – in particular, the criterion-oriented mechanism outlined in Chapter III and the concept of type 3 processing. Here also, there is scope for more research. One potential way of comparing strategy-oriented versus criterion-oriented mechanisms would be to examine the effects of sudden, unexpected, time pressure on cue usage and choice performance. The reason being that sudden unexpected time pressure would presumably result in poor performance if *a priori* strategy selection was employed. This is because the selected strategy would not match the sudden change in environment brought about by the onset of new time constraints. Whereas, if deliberation occurs as outlined in a default-interventionist manner as presented in the sequential sample model, then the preferences states gathered up until that point (beginning more heuristically and finishing more normatively) would provide an optimized response to any level of sudden unexpected time pressure. This presents itself as an interesting future direction as a response to the findings and issues in Chapter V.

An important limitation of the sequential sample model was its ability to capture the presence of bias under no-time pressure conditions. As discussed in Chapter V, this limitation is clearly due to the simplicity of the model as such a finding can be accounted for via dual-process theory. Therefore, as I discussed in Chapter V, it is important to note that the failures of this model do not necessarily reflect weakness in dual-process theory. Rather it reflects limitations of the quantitative model in its ability to capture the nuances of dual-process theory as a whole. For example, there are some tasks which appear to be stubborn sources of type 1 bias (see Evans, Handley & Bacon, 2009) and the sequential sample model I used does not differentiate between types of tasks. A potential future direction therefore, would be to attempt to capture the interplay between different types of type 1 biases and volitional control. Indeed, Stanovich's (2011) taxonomy of cognitive biases with respect to the reflective mind (type 3 processing) would provide an interesting basis for developing such a quantitative model of time pressure.

Bounded Visual Search: Motivation and Biases

In the domain of visual search decision-making, dual-process literature is also neglected. This is perhaps unsurprising as many vision theorists appear to limit their scope to the study of low-level cognitive processes. However, I believe that higher-level cognitive factors, such as expectation and motivation, are critical to visual search performance and highly relevant in the more applied domains related to visual search. One area of particular interest, which relates to the findings of Chapter VI, is that of the target-prevalence effect (see Wolfe, Horowitz, Van Wert, Kenner, Place, & Kibbi, 2007, for review). Many theories used to explain this effect relate to low level explanations of perceptual sensitivities (i.e. non-volitional explanations). However, the fact that I demonstrated shifts in signal detection theory beta values based on motivational and expectation cues indicates that higher level cognitive factors could be equally involved. Furthermore, the fact that the expectation bias had an effect in both the valid and invalid conditions indicates that it was not the learnt validity of the cues that resulted in the bias but rather the expectation of validity.

The notion of type 3 processing and the idea that search effort can be bounded seems an interesting new direction for the domain of visual search. A major question in the domain is how individuals decide when to stop searching for a target (Chun & Wolfe, 1996). This decision has clear parallels with evidence gathering issues discussed in Chapter IV and the tradeoffs associated with accuracy versus efficiency. Furthermore, given that our visual system employs a great deal of top-down processing, assessing the extent to which we can remove biases through motivation or increase the potential for bias under time constraints seems an interesting domain. Indeed, given that many important jobs involve a degree of decision-making and visual search (e.g. Airport baggage security, medical x-rays, forensic fingerprint analysis) assessing the potential for bias and volitional control seems incredibly important.

Limitations of the Sequential Sample Model and Future Directions

As discussed above, I see dual-process concepts, and especially the recent proposal of type 3 processing, as being useful for a much broader range of domains than it is currently used. The application of a quantitative model to represent some of the aspects related to type 3 processing, by implication, may also be useful. However, in this thesis I discovered some important limitations with the modelling approach I employed. In particular, it was generally found that the type 2 processing captured by the model was highly simplistic. In the model, type 2 processing and deliberation over time was represented simply by an average drift rate. Therefore, in many experiments, while dual-process theory could explain the results there was a gap between these explanations and the manner in which the model attempted to capture them. This was necessary to preserve a parsimonious approach in the early stage. However, based on the results of this thesis, I believe that some of the deeper aspects of type 2 processing could be captured in a sequential sample model through a more complex mechanism. The first would be to attempt to form some connection between the strategy-oriented mechanisms of the adaptive decision-maker framework (Payne, Bettman & Johnson, 1988, 1993) that I discussed in Chapter III and the criterion-oriented mechanism used to account for type 3 processing in the current model. The second would be to include some more principles from the dual-process literature as discussed in Chapters IV and V. This new model could then be assessed in further experiments.

Lee and Cummins Model of Adaptive Decision-Making

As discussed in Chapter III, the host of studies performed by Payne, Bettman and Johnson (1988, 1993) and those reviewed by Kunda (1990), showed that decision-makers adapt their type 2 strategies according to the time available. As far as I am aware, Lee and Cummins (2004) were the first to propose a formalisation adaptive strategy selection under a sequential sample model paradigm. In their model they considered that Payne and colleagues' (1988, 1993) view of decision-making and its various strategies might be modelled using a sequential sample framework. They posited that different choice cues may have different levels of validity, and we might use this as a guide for our strategy selection.

From Lee and Cummins (2004), cue validity for the *i*th cue is the sum of the correct decisions made by the *i*th cue (+1) divided by the total number of decisions made by the *i*th cue (+2).

$$\hat{v}_i = \frac{correct_i + 1}{total_i + 2} \quad . \qquad [3]$$

Using equation 2, the log-odds of each decision can be determined, where v_i indicates the validity input for the *i*th cue. The first sum is across all cues favouring choice A, and the second sum is across all cues favouring choice B.

$$L_{AB} = \sum_{i \in FA} \ln\left(\frac{\hat{v}_i}{1-\hat{v}_i}\right) - \sum_{i \in FB} \ln\left(\frac{\hat{v}_i}{1-\hat{v}_i}\right). \qquad [4]$$

Given positive log-odds, the decision-maker selects choice A over choice B. Given negative log-odds, the decision-maker selects B over choice A. A log-odds of zero results in a random guess. Lee and Cummins (2004), in accordance with the motivated reasoning literature (Kunda, 1990), argued that we tend to limit our cognitive effort, and they argued that we ought to do this by using high validity cues first. Therefore, a simple analytical strategy may be employed by using only the highest validity cue. This decision strategy is the *take-the-best heuristic* (TTB) (Gigerenzer & Todd, 1999; Gigerenzer & Goldstein, 1996). If, however, we examined all the cues irrespective of the validities, our decision strategy approximates the normative *rational (RAT)* strategy.

The critical step taken by Lee and Cummins (2004) was the inclusion of an accumulative paradigm derived from sequential sample models. With this, decision-makers can vary which strategy they use through manipulations of a decision threshold. As the decision-makers process the information from high validity cues down to low validity cues, they form preference states which accumulate over time. The threshold determines both the strategy that was employed and the point at which searching stops and the choice is made. Given a low threshold, the preference state generated from the initial cues (TTB-like strategy) may be enough to make a choice representing a quick heuristic-style decision. Given a high threshold, more preference states must be accumulated both increasing decision time and approaching the RAT model. Such a theory was able to successfully differentiate between TTB and RAT decision-makers.

A subsequent study by Bergert and Nosofsky (2007) provided further support for such a hybrid model. Importantly, however, Bergert and Nosofsky went further than Lee and Cummins by relaxing some of the assumptions of the strong forms of TTB and RAT which they felt were not psychologically plausible. Firstly, they relaxed the assumption that individuals are always able to learn to use optimal feature weights and allowed for individuals to occasionally make mistakes in their assignment of weights to cues (e.g. Newell & Shanks, 2003). Indeed, they were keen to point out that calculating cue validities for each dimension requires a great deal of memory capacity and experience within the domain (e.g., Newel, 2005). Bergert and Nosofsky proposed a generalised probabilistic approach to cue ordering. In order to do this, they simply suggested that the probability that a cue will be inspected would approximate the weight of the cue, thus the original deterministic cue ordering would now be probabilistic depending on a response scaling parameter, γ.

Both Bergert and Nosofsky (2007) and Lee and Cummins (2004) allow a variation in strategy to arise from one simple model depending on the decision threshold. Lee and Cummins's (2004) version represents the more prescriptive version and Bergert and Nosofsky's (2007) version represents the more descriptive version. Thus, in the same way that the sequential sample model introduced in this thesis represented a shift from more type 1 oriented responses to more type 2 oriented reasoning; the Lee and Cummins approach can model shifts from more heuristic type 2 strategies to more normative type 2 strategies. A low threshold would mean a more simplistic/heuristic type 2 strategy, whilst a high threshold would mean a more complex type 2 strategy. Furthermore, the freeing of the cue weights by Bergert and Nosofsky (2007) means that ordering could occur through both intentional strategy and the more generalised assumption of random attention effects described by the strict sequential sample models.

Integrating My Approach with the Lee and Cummins Approach

Importantly, this approach eliminates the optimisation problems with the traditional adaptive decision-maker approach I outlined in Chapter III with regards to *a priori* strategy selection. Decision-makers do not have to select a certain strategy but can simply increase their strategy complexity over time, by considering more cues, until the threshold is met. Although Lee and Cummins do not refer to it in the same terms, their threshold mechanism is essentially a mechanism for mediating type 3 processing, just as it is in the model I presented in Chapter III. In comparison to the sequential sample approach I applied, the Lee and Cummins approach is not a model of dual-processes, but rather only models type 2 processing strategy selections. While the sequential sample model I employed broadly separated early versus late information based on type 1 and type 2 responses, the integration of initial type 1 processing biases with Lee and Cummins' (2004) more sophisticated representation of type 2 strategy adaptation would be a potentially useful next step.

Figure 1 shows this proposed development. In the sequential sample model described in this thesis (Figure 1A), a drift rate summarises all type 2 processing. However, this type 2 processing could be replaced by Lee and Cummins (2004) theory (Figure 1B) to generate a more nuanced representation of type 2 processing in JDM. Importantly, this new version of the model (Figure 1C) would describe how it might be possible to shift from a type 1 response to a more type 2 driven, but still heuristic processing (e.g. TTB) behaviour, all the way to a fully normative type 2 approach (e.g. RAT) simply through the manipulation of a single threshold parameter based on the satisficing principle.

Integrating Hypothetical Thinking Principles

One issue I discovered with the sequential sample model was that the impact of type 1 processing was only captured as a shift in the z parameter. However, as discussed in some of the dual-process explanations of the experimental findings, type 1 processing can have a much greater effect than simply biasing response tendencies (see Stanovich, 2011 for an extensive review of these effects). One in particular is the notion that type 1 processing can direct type 2 processing attention (Evans, 2007a; Stanovich, 2011). Stanovich (2011) describes this as serial associative processing whereby the processing may be slow, effortful, and deliberate (indicating type 2 processing) but automatic connectionist links are made (type 1 processes) leading the mind from thought to thought. Thus, while evidence processing might involve type 2 processing, the direction of attention or choice of what evidence to examine first might be directed, in part, type 1 processing.

The sequential sample model proposed in this thesis could not represent this and the Lee and Cummins extension only allows the ordering of cues for examination to be achieved via some assessment of validity. Therefore, I propose that, in addition to type 1 processes affecting the *z* parameter, the type 1 processing could also be allowed to impact on the Lee and Cummins (2004) mechanism via the relevance and singularity principle by determining the order in which cues are examined. Both Bergert and Nosofsky (2007) and Lee and Cummins (2004) considered the assessment of cue validity as determining the order in which cues are examined. However, dual-process theories such as the relevance principle could also play a role in this ordering of cues such that the TTB heuristic is not just driven by a formal estimation of cue validity, as indicated by Bergert and Nosofsky (2007) but also by type 1 processes and the initial mental model (see Figure 1C). With this mechanism in place, the role of early type 1 processing would not simply be to push preference states towards or away from certain choices, but the initial preference state could be allowed to influence the focus of the early type 2 processing. The concept of serial associated cognition with a focal bias, seem to be important in evidence gathering and seems relevant to Chapter IV. Therefore determining whether these concepts can be integrated with the kind of mechanism Lee and Cummin propose, may be an interesting next step.

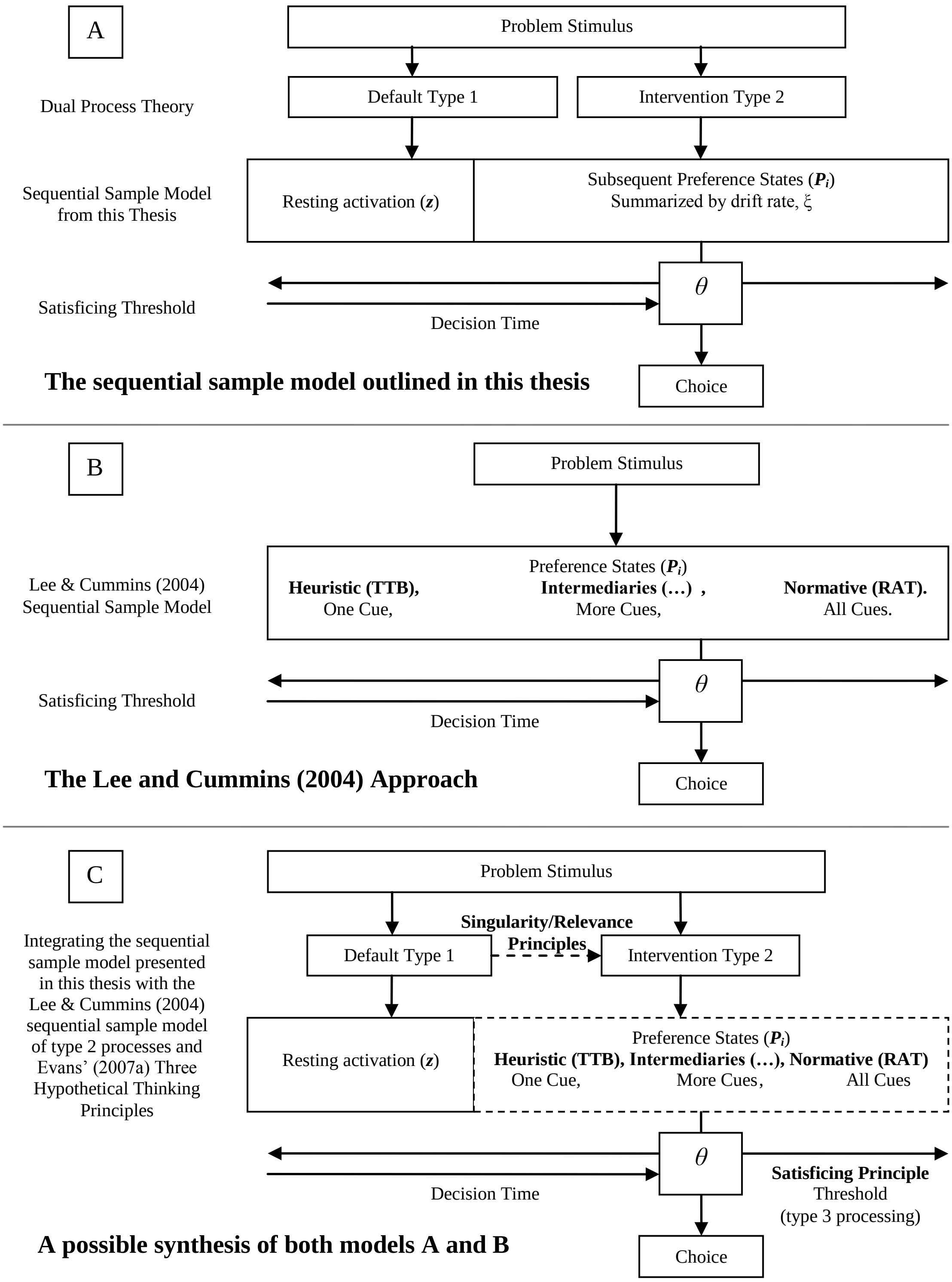

Figure 1. A depiction of (A) the sequential sample model from this thesis, (B) Lee and Cummins sequential sample model of adaptive decision making, and (C) how both could be combined by using a Lee and Cummins (2004) approach to type 2 processing and including other aspects (see below) such as Evans' (2007a) singularity and relevance principles (both shown as dotted, rather than, solid lines).

The consideration of the impact of type 1 processing on the direction of type 2 processes echoes Tetlock's (1983) earlier biased assimilation interpretation of primacy effects discussed in the introduction (Chapter I). This theory states that people form instant impressions based on the information (i.e. type 1 processing), and then later (type 2) processing of the information is interpreted according to this mental frame (Tetlock, 1983). Thus, the strict separation of type 1 and type 2 processing designated in the original model (Figure 1A) perhaps demonstrates the greatest limitation of the sequential sample model employed in this thesis. However, developments in the direction shown in Figure 1C may begin to overcome this limitation. Indeed, returning to the initial aim of this thesis, such a mechanism may provide a fruitful way of approaching the modelling of primacy effects and the role of early versus late information in JDM.

Modelling Expertise

This new model could also be applied to other JDM research domains, such as examining the role of dual-processes in expert versus novice decision-making. Evidence has confirmed that as individuals become more familiar in a domain, they invariably develop a more detailed mental model (Hutchinson, Raman, & Mantrala, 1994). For example, Spence and Brucks (1997) demonstrated how professional experts tend to employ fewer, but more diagnostic (highly valid) attributes when estimating the market value of houses, based on multi-attribute descriptions, than novice undergraduates students. Accordingly, experts are better able to choose the most appropriate attributes when making decisions, whereas novices are more likely to consider more attributes and make decisions based on the weight of evidence (Hutchinson & Einstein, 2008). For example, Dellaert and Stremersch (2005) demonstrated how expertise in computer technology enabled experts to better choose the optimal computer components for their needs than novices.

The dual-process framework seems highly applicable to the domain of expertise in decision-making (see Evans, 2008). In particular, I believe that the integration of the hypothetical thinking principles into the proposed new modelling framework presented in Figure 1C may be of use in this domain. Experts are better able to form useful initial mental models, based on type 1 processing, and are able to identify high validity cues to examine. In terms of the proposed model in Figure 1C, this would result in effective TTB strategies driven by a positive focal bias from type 1 processes. Such a decision-process would be predicted to reach the satisficing threshold level using fewer cues (just as selective exposure did in Chapter IV) but without reduced accuracy. Novices would be modelled as being unable to effectively order the information by validity and have poor initial type 1 mental models. Therefore, they would simply gather evidence almost randomly over time until the accumulation is sufficient to reach their satisficing threshold. This model would capture why it is that novices tend to demonstrate more holistic and broader evaluative strategies and experts demonstrate more "surgical" and focused decision strategies (Hutchinson & Einstein, 2008) almost without awareness. Figure 2 shows a conceptualization of an expert (E) compared to a novice (N) in deciding whether or not to purchase a particular product.

Note that the mean preference state change, or drift rate, for the expert (DR_E) is steeper resulting in a quicker decision, and it has a lower standard deviation (SD_E) reflecting the internal consistency of the highly valid cues he chooses to consider. However, for the novice, the deliberation involves consideration of many more cues, reflected by the lower drift rate (DR_N), which have less internal consistency reflected by the higher variation in preference state (SD_N). Indeed, due to this fluctuation, the novice almost disregards the product for purchase on considering the second attribute (P2). Figure 2 demonstrates how some of the important characterizations of experts and novices can be represented by this conceptualization. Importantly, it also could be of value in understanding how a novice might gradually improve performance over time (i.e. learning/developing expertise). As they begin to be better able to form useful initial mental models from type 1 processing, and also direct their attention towards the most diagnostic attributes (early type 2 processing), they would be predicted to improve their deliberation times and accuracy. Testing these models' predictions regarding novice and expert decision-making would be another interesting research direction stemming from the work in this thesis.

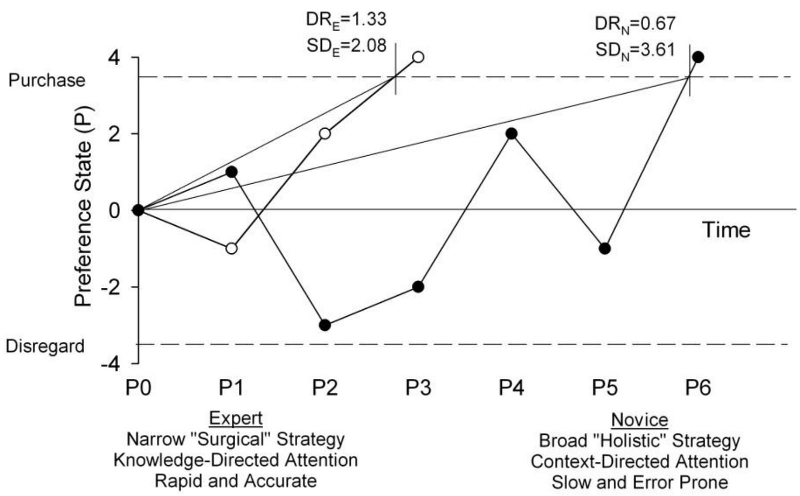

Figure 2. A conceptualization of an expert and a novice deliberation process for a purchase decision

Extending to Multi-Alternative Decision-Making

An important limitation of the sequential sample model outlined in this thesis, and indeed the Lee and Cummins extension proposed in this chapter, is the fact that it can only model one hypothesis at a time. This results in a model which can at most distinguish between two choices. The question remains, therefore, as to how best to model multi-alternative decision-making. One solution would be to introduce extra dimensions for each choice such that, rather than modelling the preference for one choice over another (i.e. a two-dimensional choice), the preference state could be across three, four, five, etc. dimensions, one for each alternative. However, while this would seem the logical step, this may contravene some principles of dual-process theory. For example, Evan's (2007) singularity principle argues that we do not consider all alternatives in parallel (i.e. what would be modelled using a multidimensional sequential sample model) but rather, we consider one hypothesis at a time. Indeed, Chapter IV, which focused on the theories relating to biased predecision processing, certainly supports this view as individuals tend to focus on only one early favourite versus the rest rather than considering all alternatives equally.

Accordingly, a solution might be to consider a nested or iterative sequential sample model approach in which individuals select an initial favourite alternative (perhaps based on type 1 processing) from all the available alternatives. This early favourite is evaluated against the hypothesis that it is the best alternative in a simple two-dimensional sequential sample model; i.e. one threshold for confirmation and one for disconfirmation. If the preference state reaches the confirmation threshold for that initial alternative then this choice will be selected. If the disconfirmation threshold is met then the individual must reconsider the options and choose another alternative (i.e. form a new hypothesis to test). This would be modelled via another subsequent sequential sample model within the same decision deliberation. The number of dual-alternative sequential sample models required for a single choice, would therefore depend on the number of hypotheses generated during deliberation. Accordingly, whereas the total deliberation time in a single multidimensional sequential sample model would be some function of the number of samples taken, in nested sequential sample model deliberation, the total deliberation time would be the sum of the samples taken by each run of the sequential sample model generated during the choice.

This nested modelling approach not only reflects the singularity principle but also the evidence from the biased predecision processing literature. The literature suggests that multi-alternative decisions are not a comparison of all alternatives but rather the evaluation of an initial favourite alternative against the alternative hypothesis that it is not the best. This nested modelling approach is perhaps a more accurate representation of Evan's (2006) representation shown in Figure 1 in Chapter I whereby single mental models are considered one at a time and evaluated against the satisficing principle in an iterative fashion. This concept of nesting sequential sample models used in conjunction with the Lee and Cummins extension presents some interesting future research directions for the quantitative modelling of dual-processes.

Final Conclusion

The dual-process notion of rapid and automatic processing as well as a slower, effortful consideration of information involving working memory clearly has implications for many aspects of psychology, and in particular the psychology of judgement and decision-making. The advances in dual-process theory, such as the notion of type 3 processing, demonstrate further avenues for understanding JDM behaviour in this ever advancing theory.

The focus of this thesis has been to apply the overarching principles of dual-processes to a variety of decision-making research applications. In particular, I attempted to capture some of the basic elements of default-interventionism in a quantitative manner. The empirical studies then tested and demonstrated the extent to which this approach could be a useful way of accounting for JDM behaviour. I see this work as an attempt to fulfil Newel's vision of the future of JDM theory whereby rather than choosing from a set of different tools (toolbox hypothesis), individuals adjust the parameters of the tool to the situation; a criterion based approach he called the "*adjustable spanner*" analogy (Newel, 2005). Of course, there are limitations of the approach employed in this thesis. In particular, the model used was a relatively simple representation of only a few basic concepts. Nevertheless, it has formed a basis for future, more complex, modelling possibilities and I have described where I see the next stage for this work.

Appendix A

Example of an Information and Consent Form

Information sheet

I am Peter Fraser-Mackenzie a PhD research student. I am requesting your participation in a study regarding [General description of Study]. [Detailed description of specific tasks and what will be required]. Personal information will not be released to or viewed by anyone other than researchers involved in this project. Results of this study will not include your name or any other identifying characteristics.

Your participation is voluntary and you may withdraw your participation at any time. *[For students:* If you choose not to participate there will be no consequences to your grade or to your treatment as a student in the psychology department*]*. If you have any questions please ask them now, or contact me at paffm102@soton.ac.uk

Signature Date

Name

Statement of Consent

I __________________________ have read the above informed consent form.

[participants name]

I understand that I may withdraw my consent and discontinue participation at any time without penalty or loss of benefit to myself. I understand that data collected as part of this research project will be treated confidentially, and that published results of this research project will maintain my confidentially. In signing this consent letter, I am not waiving my legal claims, rights, or remedies. A copy of this consent letter will be offered to me.

(Circle Yes or No)

I give consent to participate in the above study. Yes No

If applicable

Signature Date

Name *[participants name]*

I understand that if I have questions about my rights as a participant in this research, or if I feel that I have been placed at risk, I can contact the Chair of the Ethics Committee, Department of Psychology, University of Southampton, Southampton, SO17 1BJ.

Phone: (023) 8059 5578.

Appendix B

Decision Field Theory

This section will describe Busemeyer and Townsend's (1993) Decision Field Theory as a basic example of an accumulative model. It is intended that this section will summarise the concepts behind the accumulative paradigm of the decision process and provide a foundation for subsequent discussion in relation to the conclusions drawn thus far.

The theory is an attempt to develop expected utility theory from a normative theory to a more powerful descriptive theory of the decision process and can be broken down into seven sub-models. It uses subjective probability weights (Subjective EU Theory). It allows attention to fluctuate between choices, not only across trials (Random SEU Theory) but also within trials (Sequential SEU Theory). It provides a framework for explaining time pressure, motivated accuracy, and preference reversal (Random Walk SEU Theory). It attempts to describe the effects of recency and primacy effects in deliberation (Serial SEU Theory), the role of approach-avoidant gradients (Approach Avoidant SEU Theory), and finally to make quantitative time-related predictions (Decision Field Theory).

Expected Utility Theory (EUT)

Neumann & Morgenstern's (1944) *Expected Utility Theory* (EUT) states that given a two choice problem with two potential states there are four outcomes. The expected utility of each action, A_i, is the sum of the probabilities of each state, $p(S_i)$, multiplied by the payoff gained from that state, u_i. This is referred to as the valence of each action. The difference, d, between the two actions valences indicates what action should be chosen.

Subjective Expected Utility (SEU) Theory

As far back as 1713, Jakob Bernoulli observed that probability is a degree of belief or human self-awareness, as opposed to the actual state of the world (Berthoz, 2006). Rarely is it true that we have complete knowledge of the chance of each state occurring. Indeed, Simon (1983) rather mockingly describes this as Olympian rationality, i.e. that it is closer to the abilities of the gods than of man. Therefore, the first stage of decision field theory stipulates that each potential return be assigned a subjective probability weight. The payoff of, say 200, from action A_y is given a weight that depends on the subjective expectation of event S1 occurring. The weight is denoted $w(S1)$ and is a proportion between 0 and 1. Busemeyer and Townsend (1993) propose that this weight reflects the amount of attention given to event S1 by the decision-maker at that point in time. This attention weight replaces the probability parameter in the expected utility theory. So, for action A_x and A_y the SEU would be as follows.

$$v_x = w(S1) \cdot u(-500) + w(S2) \cdot u(+500), \tag{5a}$$

$$v_y = w(S1) \cdot u(+200) + w(S2) \cdot u(-200), \tag{5b}$$

$$d = v_x - v_y, \tag{5c}$$

The valence difference, d, between the two indicates the direction of action. So action A_x is chosen when $d > 0$, Ay is chosen when $d < 0$, and $d = 0$ results in indecision or random guess.

Random SEU Theory

However, the EUT did not account for within and between trial random differences; it is still a deterministic model. Therefore, it would predict the same outcome on all trials, which is not empirically supported. Busemeyer and Townsend (1993) argued that fluctuations in attention cause random variance as attention is correlated with the subjective estimation of chance. Random SEU allows for variation in attention between events across trials. Therefore, the subjective probability weight can differ for the same problem on different trials, allowing differing action preferences on different trials. The new randomised subjective weight is denoted as $W(S_i)$ resulting in a new SEU for each action called the valence for action (V_i). Now, rather than a valence difference, we have a preference state, P, which can change between trials.

$$V_x = W(S1) \cdot u(-500) + W(S2) \cdot u(+500), \quad [6a]$$

$$V_y = W(S1) \cdot u(+200) + W(S2) \cdot u(-200), \quad [6b]$$

$$P = V_x - V_{y,} \quad [6c]$$

Sequential Sampling SEU Theory

The Random SEU theory is based upon a single sample of valence difference on any trial. Sequential sampling SEU theory turns this static model into a dynamic model by allowing a sequence of samples to be taken and accumulated within a trial, thus introducing deliberation and the temporal nature of decision-making. Preference can now fluctuate within a single trial and not just between them, resulting in multiple preference states in each trial.

$$\text{Initial preference state, } P(1) = [V_x(1) - V_y(1)], \quad [7a]$$

$$\text{Second preference state, } P(2) = P(1) + [V_x(2) - V_y(2)], \quad [7b]$$

$P(n\text{-}1)$ is the preference state after n-1, and $[V_x(n) - V_y(n)]$ is the new valence difference. These preference states accumulate until an inhibitory threshold or critical level, θ, is reached. So a positive preference state indicates a momentary preference favouring action A_x. However, unlike the last two stages, action is not taken when the preference state is merely non-zero, rather, $P(n)$ must reach θ. The total number of samples required to meet this threshold is a random variable, N, and response time is an increasing function of N. Now the valence difference, d, is representative of the mean change in preference produced by each new sample.

$$d = \sum[V_x(n) - V_y(n)] = \sum[P(n) - P(n-1)] = v_x - v_{y,} \quad [8a]$$

The variance of the valence difference is as follows.

$$\sigma^2 = \mathrm{Var}[V_x - V_y] = \sigma_x^{\ 2} + \sigma_y^{\ 2} - 2 \cdot \sigma_{xy} \quad [8b]$$

Where the variance for action x is,

$$\begin{aligned}\sigma_x^{\ 2} &= \Sigma[(V_x - v_x)^2] \\ &= w(S1)\cdot[u(-500) - v_x]^2 + w(S2)\cdot[u(500) - v_x]^2 \quad [8c]\end{aligned}$$

The variance for action y is,

$$\sigma_{y2} = \Sigma[(V_y - v_y)^2]$$
$$= w(S1) \cdot [u(200) - v_y]^2 + w(S2) \cdot [u(-200) - v_y]^2 \qquad [8d]$$

The covariance for this example is,

$$\sigma_{xy} = \Sigma[(V_x - v_x) \cdot (V_y - v_y)]$$
$$= w(S1) \cdot [u(-500) - v_x]^2 \cdot [u(+200) - v_y]$$
$$+ w(S2) \cdot [u(500) - v_x]^2 \cdot [u(-200) - v_y] \qquad [8e]$$

The probability of choosing action x over action y is[1],

$$Pr(A_x,A_y)=F[2 \cdot (d/\sigma) \cdot (\theta/\sigma)]. \qquad [9]$$

The threshold, θ, mediates the amount of deliberation required to make a decision. Low thresholds result in rapid, error-prone judgements and high thresholds result in slower more accurate judgements. Therefore, this model has the ability to represent speed-accuracy trade offs. In addition, rather than a decision-maker being faced with a three-choice decision, decide x, decide y, or keep deliberating, deliberation automatically occurs until the threshold is met. This means that decisions form in a more organic, continuous, and accumulative way.

Random Walk SEU Theory

Critically, Busemeyer and Townsend then considered that not all decisions begin in an unbiased fashion and, as a result, the start point or anchor, *z*, might not always begin in a neutral position. Therefore, the decision-maker may have an initial bias. This means that the early preference states begin closer to one threshold than the other, increasing the likelihood of it being chosen. Furthermore, the bias influences response times as there is a shorter distance for the accumulation of preference state.

$$P(0) = z,$$
$$P(n) = P(n - 1) + [V_x(n) - V_y(n)]$$
$$= z + \Sigma_k [V_x(k) - V_y(k)],\ k = 1, 2, \ldots, n, \qquad [10]$$

Figure 4 shows a decision task in which the information drives a general drift towards decision *x*. The figure shows a case when there is a bias towards choice *y* compared to a case in which there is no bias. As a result of the bias, the number of samples required to reach the *x*-choice threshold increases and thus the probability of choosing *x* decreases. Therefore, the model states that a bias like this has an effect on both decision likelihood and response times.

---

[1] Where F is the standard logistic cumulative distribution function, $F(x) = 1/[1+\exp(-x)]$.

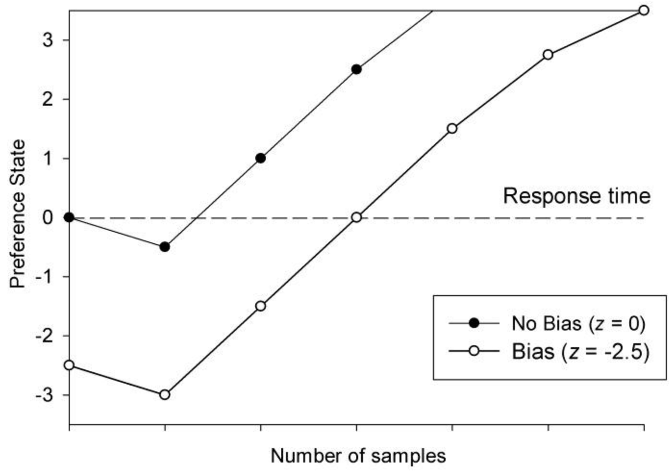

Figure 1A. *A biased and an unbiased decision process. Note that preference reversal occurs when a bias exists depending upon the number of samples used to make the decision as dictated by the decision threshold, and the quicker correct decision RT without a bias.*

Linear System SEU Theory

The linear system theory argues that the order in which information is attended to, affects how it is processed. Specifically, the effect of the valence difference depends on whether it occurred early or late in the deliberation. This includes a new parameter, *s*, which is the growth-decay parameter. If this parameter is between zero and one then we find a recency effect where there is slow preference movement in initial deliberation, yet it increases in speed as the deliberation nears the threshold. Whereas, if it is below zero then we find a primacy effect defined by rapid travel towards the threshold in early deliberation, yet it slows as it nears the critical value.

$$\begin{aligned} P(\mathrm{n}) &= (1-s)\cdot P(\mathrm{n}-1) + [\mathrm{V_x(n)} - \mathrm{V_y(n)}] \\ &= P(\mathrm{n}-1) + [\, d(\mathrm{n}) + \varepsilon(\mathrm{n})] \end{aligned} \qquad [11]^{[2]}$$

This can be used to model reductions in the weight of information over time. Belief perseverance showed that participants weight early information as more important than late information. Therefore, this too can be used to make predictions about cognitive biases.

Approach-Avoidance SEU Theory

The approach-avoidance SEU adds another parameter, *c*, the goal gradient. This is comprised of an approach gradient which determines the effect of gains, and an avoidance gradient which determines the effects of losses, on the preference state as it nears the threshold. The theory stipulates that as the deliberation nears the threshold, the consequences of a particular action become more salient and there may be differences between gains and losses in this effect. For avoidance-avoidance

[2] ε, refers to the residual where $\varepsilon = P - d$

conflicts, c is positive which causes preference state to vacillate between choices, slowing the whole deliberation process. For approach-approach conflicts, c is negative which causes preference state to progress towards the threshold faster, in turn, increasing decision time. The gradients are incorporated as follows.

$$P(\mathrm{n}) = (1\text{-}s) \cdot P(\mathrm{n}\text{-}1) + [\mathrm{V_x(n)} - \mathrm{V_y(n)}]$$
$$= (1\text{-}s) \cdot P(\mathrm{n}\text{-}1) + [\, d(\mathrm{n}) + \varepsilon(\mathrm{n})]$$
$$= [1\text{-}(s+c)] \cdot P(\mathrm{n}\text{-}1) + [\delta + \varepsilon(\mathrm{n})], \qquad [12a]^{[3]}$$

$$\text{Where } \delta = (\mathrm{v_{gainsX}} - \mathrm{v_{gainsY}}) \cdot (1 - \mathrm{a} \cdot \theta) + (\mathrm{v_{lossX}} - \mathrm{v_{lossY}}) \cdot (1 - \mathrm{b} \cdot \theta), \qquad [12b]^{[4]}$$
$$c = b \cdot (\, v_{lossX} + v_{lossY}) - a \cdot (v_{gainsX} + v_{gainsY}) \qquad [12c]$$

Decision Field Theory

This is the final stage of the theory that introduces a time unit, h, which represents the amount of time it takes to retrieve and then process each sample of valence difference. The deliberation time, t, is therefore the number of samples, n, multiplied by this time unit parameter, h.

$$P(\mathrm{n}) = (1\text{-}s) \cdot P(\mathrm{n}\text{-}1) + [\mathrm{V_x(n)} - \mathrm{V_y(n)}]$$
$$= [1\text{-}(\sigma+\psi) \cdot \eta] \cdot \Pi(\tau - \eta) + [\delta \cdot \eta\, \varepsilon(\tau)] \qquad [13]$$

[3] δ, refers to the mean valence input and is similar to the mean difference d in the linear updating rule, but it includes the effect of approach and avoidance gradient weights, i.e. a positive mean valence input results in a positively driven preference state and a negative mean valence input results in a negatively driven preference state.

[4] a is the goal gradient for gains, and b is the goal gradient for losses. These both contribute to the goal gradient parameter, $c(a,b)$.

Appendix C

R Code for Simulations in Chapter III

```
#R-Code for the sequential sample model of dual-process mediation
using a criterion-based system for representing type 3 processing.
pptN=NULL
pptC=NULL
plotlength=80
#setup graph
plot(1:plotlength,rep(NA,plotlength),type='o',xlab="Deliberation
Time (N Samples)",ylab="Preference State",ylim=c(-25,25))

coefs=NULL
for(i in 1:100){

#Set up parameters#
history=NULL
s=4 #drift volatility
d=1 #drift rate
z=0 #type 1 bias
T=20 # threshold

#Type 1 Response#

P=z
history<-c(history,P)

#Type 2 Response#
#Assess whether Type 1 response passes threshold (Feeling of
Rightness)
#else perform algorithmic/type 2 thinking over time until threshold
is met

while(abs(P) <= T) {
P<-P+rnorm(1,d,s)
history<-c(history,P)
}

#deliberation time#
N<-length(history)

y<-c(history,rep(NA,plotlength-N))
x<-1:plotlength

if(P>0) lines(x,y,col="#0000ff50") else lines(x,y,col="#ff000050")

drift<-lm(history~seq(1:N))
coefs<-rbind(coefs,drift$coefficients)


pptN<-c(pptN,N)
C<-ifelse(P>0,1,0)
pptC<-c(pptC,C)
}

mean(pptC)

#Positive#
```

```
median(pptN[pptC==1])
sd(pptN[pptC==1])
length(pptN[pptC==1])
sd(pptN[pptC==1])/sqrt(length(pptN[pptC==1]))

#Negative#
median(pptN[pptC==0])
sd(pptN[pptC==0])
length(pptN[pptC==0])
sd(pptN[pptC==0])/sqrt(length(pptN[pptC==0]))

#plot graph
title(paste(round(mean(pptC)*100,2),"% Choose A over B", sep=""))
text(plotlength-1,T+3,"A",col='blue',cex=2)
text(plotlength-1,-T-3,"B",col='red',cex=2)
abline(v=median(pptN[pptC==1]),col='blue',lwd=2)
abline(v=median(pptN[pptC==0]),col='red',lwd=2)
abline(h=T,lty=2)
abline(h=-T,lty=2)
```

Appendix D

VORTECH 1100

£35 - £40

- Weight: 86 g (with VORTECH Battery BL-5C)
- Dimensions: 106 mm x 46 mm x 20 mm
- Talk time: Up to 2 - 4.5 hours
- Standby time: Up to 100 - 400 hours
- Features: Built-in flashlight, Durable cover with anti-slip sides, Sleek silicone keymat with large keys, Reminders and alarm clock, Changeable Xpress-on™ covers
- Networks: GSM 900, 1800
- This is a low cost budget phone with all the basics required for making phone calls and texting. The Vortech 1100 phone lets you conduct business in confidence and style – in the shops or on the move, during the mid-morning rush or at midnight. New features like the long-lasting battery and a durable design help you work even smarter.

1 Star reviews

i. I absolutely hated this phone. I used to have a nice top of the range phone but had to use this as an interim measure. It was a big step down from what I was used to. It was bigger and heavier, which is surprising as there was less in it and it looks pretty ugly. I also found it difficult to use in loud environments because the sound quality was so bad. In the end I got rid of it as soon as I could. I would never get one of these again! Don't buy this phone, it is absolutely horrendous!

ii. This phone annoyed me. It didn't have a colour screen and I hated getting it out in public. I always thought people were laughing at me for having such a cheap nasty phone. In the end I threw it away, because I was so annoyed with it, and bought a better one. It was the first time I had bought a Vortech and did so because I had heard that they were a good make. However, on the basis of this phone I might never buy a Vortech again. This phone was the worst phone in the world!

iii. I could not stand this phone. It was the worst phone I have ever owned. Every time I looked at it I wanted to throw it away. I'm just glad that it was so cheap. I would never have bought this if it had been any more expensive. It was awkward to use and the text button functions took me ages to learn. In the end all I used it for was a nice sized torch. In fact if you want a torch and a paper weight all in one then buy this phone! If you want a mobile phone, then get something else.

2 Star reviews

i. I didn’t like this phone very much. I only had it a short while because I had lost my other, better one and needed a cheap phone in between. I suppose cheap is what it is. If you want a cheap phone that you are not too bothered about then get this one. I suppose if you’re just looking for a functional simple phone then this would be fine. For me, however, I wanted a phone with more stuff like an MP3 player or even an FM radio would be nice. I really didn’t like this phone much.

ii. I was not happy with this phone. The first one I bought broke within a few days and I had to send it back. The second one I had seemed to work fine, but it was just a bit tacky and rubbery. It did the job, although sometimes it was a little hard to hear in loud situations. I wouldn’t buy this again, unless I had to, just because there are better phones around. I know Vortech is a good make, and I suppose it wasn’t too bad, but I would not buy it again. There are better ones around.

iii. I had trouble liking this phone. It was quite strong and seemed to bounce rather than break when I dropped it. But it was not very good. It was made cheaply, which was reflected by the price, and as such the sound quality was pretty poor, especially in loud, busy places. I could not work out how to use the calendar function and texting was a bit of a nightmare. Maybe it was me or maybe the phone but we just could not get on with each other! I won’t get it again.

3 Star reviews

i. This phone was okay for the short time I owned it. I used it while I was waiting to get a better, more expensive one. It was cheap and reliable and did what I needed it for. I never really had any problems with it. The battery was pretty long lasting, probably because it only had simple things to do, i.e. there was no battery wasting MP3 player or anything like that. I was a simple phone with the added benefit of having a torch on it! It was okay I suppose, pretty functional; did the job.

ii. I didn’t mind this phone. It was simple and easy to use, I never had any problem with it. I am waiting to get a better one but at the moment I am reasonably happy using it for the time being. I mainly used it for just phoning and so it did the job required without any fuss. The battery life was fairly good and, seemed a bit sturdier than most, which was nice for a change! In all, it was okay as a phone but not special. The torch was quite a nice addition but I never really used it!

iii. This Vortech was okay. I have had other phones in the past which have been a hell of a lot worse, but this was reliable and functional. I use a phone to make phone calls and this phone did exactly what I needed it for. Yes there are better phones around with better sound quality but they are a lot more expensive. In all this was a simple okay phone which anyone, especially the less technologically minded, me included, can use. This phone was okay but nothing really special.

4 Star reviews

i. I really liked this phone because it was simple and reliable. I never once had any problem with it, and to be honest it was quite nice to have a phone without all those extras which I'd never use anyway. The torch was good too; I always found it useful when trying to find the key hole for my car at night. In fact the torch might be the only accessory I have ever used on a mobile phone. I don't even know what an MP3 is, let alone Bluetooth! I liked this phone, it was good and reliable.

ii. I liked this phone a lot. It did everything I asked for from a mobile phone. I could set up reminders and write text messages as well as making phone calls. There were even a few games that I could play on the train on the way to work! Also it has interchangeable covers; I have lots of different ones now. Why spend hundreds of pounds when you can have this one? This phone was a good buy in my view. It's not the most hi-tech but it does what I need it for, so I'm happy.

iii. I liked this phone. It was so easy to use. Some of the other phones that I have had in the past have had so many other things on them, that I had no idea what to do with most of them. With this phone it was simple to make phone calls and I could write text messages as well. I have bought more expensive phones in the past but they did far more than I, or as far as I could see anyone else, needed them for. This one was cheap and cheerful! This phone was pretty good overall.

5 Star rating

i. I absolutely loved this phone. It was my first ever mobile phone and I forged a loving relationship with it. I even named it! It was just so simple to use. I was worried that I would never manage to use a mobile phone because they seemed so complicated, but this one worked like a dream. It even had a torch on it; which was surprisingly useful. The screen was large and clear and I could see exactly what I was doing. The buttons were big as well. This phone was amazingly good.

ii. I adored this phone. Why oh why do people spend hundreds of pounds on these expensive phones which can practically do washing up yet are impossible to make a simple phone call from?! I have used this phone for ages and hope to never have another phone again. It is simple and not too bulky. The buttons are big enough to press, unlike other phones I could mention, and not only that but I can actually see what I'm doing. I absolutely loved this mobile to bits, it's great!

iii. This phone was amazing! I loved it so much I never want to buy another phone again. I could do everything I ever needed to do on it. I could make phone calls (the main point of a mobile phone is to make phone calls, not listen to music on!), I could text, and with 100-400 hours of standby time it is perfect for people who travel around the country a lot. If you want a simple, affordable phone then buy this one. I absolutely loved it, it was the best phone I have ever had in my life.

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