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FACULTY OF MEDICINE, HEALTH AND LIFE SCIENCES

School of Psychology

The effects of task demands and cognitive resources on information acquisition in decision making

by

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ABSTRACT
FACULTY OF MEDICINE, HEALTH AND LIFE SCIENCES
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THE EFFECTS OF TASK DEMANDS AND COGNITIVE RESOURCES ON INFORMATION ACQUISITION IN DECISION MAKING
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The Effort-Accuracy framework (E-Af) of decision making predicts that as the computational demands of a decision increase and supersede cognitive resources, the decision maker adopts increasingly cognitively-economical strategies of information processing (Payne, Bettman, & Johnson, 1993). However, these predictions have not been systematically tested, and the framework does not sufficiently distinguish between the effects of different sources of task demand (e.g. increased decision complexity vs. increased decision difficulty). This research program aimed to explore the predictions of the E-Af, through manipulating the balance between task demands and the cognitive resources of the decision maker. Specifically, it examined the effects of increasing objective levels of task demand, through both increased difficulty and complexity, on the information acquisition process underlying decision making in groups that represent three levels of cognitive resources: diminished (older adults), cognitively-optimal (young adults), and enhanced (experts). The results presented in this thesis provide broad support for the predictions of the E-Af. All decision makers adopted more cognitively-economical decision strategies as task demand increased, with the cognitively-diminished group demonstrating the most, and the cognitively-enhanced group demonstrating the least, cognitive economy. The results also suggest that both demand source and decision domain (the topic of the decision) influence the information acquisition process, and as such must be considered as a factors in future decision making research. In addition, this thesis provides an insight into both older adult and expert decision making.

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Abbreviations

A&E	Accident and emergency department
ACQ	Number of information boxes examined
ADDIF	Additive difference, or linear compensatory, model
ANOVA	Analysis of Variance
ATLS	Advanced trauma and life support handbook
CRM	Constant ratio model
DV	Dependent variable
E- Af	Effort-Accuracy framework
EBA	Elimination by aspects heuristic
EIP	Elementary information process
EQW	Equal weights heuristic
EU	Expected utility
EUT	Expected utility theory
EV	Expected value
EVT	Expected value theory
F	F ratio
FRQ	Frequency of good and bad features heuristic
GCS	Glasgow Coma Scale
JND	Just noticeable difference
LEX	Lexicographic heuristic
LEXSEMI	Semi-lexicographic heuristic
M	Mean

MANOVA	Multivariate Analysis of Variance
MAUT	Multi-attribute utility theory
MCD	Majority of confirming dimensions heuristic
mmHg	Measure of blood pressure
ms	Milliseconds
N	Sample size
p	Probability
p_1	Probability of outcome associated with a decision alternative
PATTERN	Index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing
pO2	Partial pressure of oxygen in the blood
PTMI	Proportion of time spent on subjectively most important attribute
R^2	Correlation coefficient
RAN or RC	Random choice heuristic
rACQ	Ratio of number of information boxes examined
rPTMI	Ratio of proportion of time pent on subjectively most important attribute
rTdTIME	Total time to decision ratio
rTperACQ	Time per acquisition ratio
s	Seconds
SAT	Satisficing heuristic
SD	Standard deviation
SEQ	Structural equation modeling
t	*t* statistic
TdTIME	Total time to decision

TperACQ	Time per information acquisition
v_1	Possible monetary gain
VAR-ALT	Variance in the proportion of time spent on each alternative
VAR-ATT	Variance in the proportion of time spent on each attribute
WADD	Weighted additive rule
WAIS - III	Wechsler Adult Intelligence Scale, version III
Z	Z statistic

Preface

Over the last 20 years, decision making research has shifted from a focus on decision outcome (good vs. bad decisions) to one on *how* humans make decisions. More recent research has concentrated on the information processing underlying decision making, which is most often operationalised in terms of the strategies decision makers employ in acquiring decision information.

One of the predominant theoretical approaches in this line of research is the cost/benefit framework of information processing, elaborated in terms of decision making by Beach and Mitchell (1978), and subsequently by Payne, Bettman, and Johnson (1993). The cost/benefit framework rests on the assumption that cognitive resources are limited; in other words, humans only have a certain amount of mental energy to apply to any given task (Kahneman, 1973; Marschak, 1968; Miller, 1956; Navon & Gopher, 1979; Park & Schwartz, 2000; Thomas, 1983). An individual's computational availability (or amount of cognitive resources) is thought to relate to the sum total of attention and working memory capacity (Kahneman, 1973). Every task involves both certain cognitive costs, as well as benefits incurred. In terms of decision making, the cognitive costs may be defined by the information acquisition process (specifically the decision strategy employed). The benefits relate to decision accuracy, or the probability of making a 'good' decision.

The cost/benefit tradeoff (or according to Payne *et al.*, 1993, the effort-accuracy trade-off) rests on the balance between task demands and the cognitive resources available to apply to those demands. Task demands of a decision are defined by its complexity and its difficulty. Factors relating to the environmental conditions in which the decision is made, factors relating to the decision structure itself, and factors relating to the individual decision maker may determine task complexity and task difficulty.

As cognitive resources are limited, task demands may exceed task resources. At this point, decision makers are driven to minimize cognitive effort whilst maximizing cognitive efficiency (Payne *et al.*, 1993). This is generally agreed to be visible in a shift to more economical decision strategies. Cognitively economical strategies demand less cognitive effort than normative strategies, and are generally non-compensatory in nature. This will be discussed further in Chapter 1, Section 1.5. The Effort-Accuracy framework (Payne *et al.*, 1993), a dominant cost-benefit model in decision making, claims that decision makers are adaptive, and will adopt increasingly economical strategies as task demand increase.

Despite a general agreement that cognitive economy is adopted in the face of increased task demand, there are many questions that remain unanswered within this framework and in this area of research. Each decision is the result of a precise balance between the task demand, and the computational availability of the decision maker. The effects of altering this balance, through both varying levels of task demand as well as computational availability, on the information acquisition process have not been studied behaviourally, on consistent decision tasks. To date, studies have focused largely on computer simulations, and even where behavioural data have been collected, they have been on isolated decision tasks. As such, mapping changes in the information acquisition process to shifts in the balance between demand and computational availability has not been done in a systematic way. In addition, there have been no qualifications or distinctions made about the precise nature of 'task demand' or 'cognitive resources.' Both concepts have been referred to along unitary scales of measurement: they are assumed to be qualitatively the same, but vary in quantity on different tasks. With regard to task demand, in previous research, task complexity and task difficulty have been assumed to increase task demand in an equivalent, quantitative way. However, it is very possible that they are qualitatively different, and as such equivalent increases in task difficulty and task complexity will result in the adoption of different decision strategies. With regard to cognitive resources, greater or less computational availability has often been linked to expertise and cognitive ageing respectively. However, expertise and cognitive ageing may not represent simply different amount of resources on a unitary scale, but may involve qualitative differences that impact on decision making.

This thesis is rooted in the information processing approach to decision making, and explores the assumptions made by the Effort-Accuracy framework (Payne *et al.*, 1993) in more detail. It attempts to begin to bridge some of the gaps in previous research as outlined above. The broad aim of this thesis is to examine how factors which determine task difficulty and task complexity affect the information acquisition process underlying decision making, namely in terms of what decision strategies are employed in different conditions. Specifically, it will explore how varying the degree of equivalence, or the balance, between the cognitive demands of the task (operationalised by decision complexity and decision difficulty) and the amount of cognitive resources a decision maker can apply to a decision, impacts on the information acquisition process underlying the decision. It will also focus on qualitative differences in concepts relating to task demand (difficulty and complexity) and concepts relating to cognitive resources (ageing and expertise).

In terms of the independent variables of interest in this thesis: decision complexity will be defined by the number of alternatives and attributes in a given decision; decision difficulty will be operationalised by time pressure; and cognitive resources are represented by cognitive ageing and expertise. In terms of the dependent variable of interest to this thesis, the information acquisition process outlines how a decision space is searched. Common patterns of information acquisition, or decision strategies, have been identified and any changes in them across different decisions will be measured.

Chapter 1 will present the theoretical foundation on which this thesis rests, in introducing normative and descriptive theories of decision making, and theoretical assumptions and work from the information processing approach to studying decision making. The external factor of time pressure will be the focus of Chapters 3, 5, 7 and 9; the internal factor of cognitive resources will be examined in Chapters 5, 6, 8 and 9, and the decision factor of complexity will be explored in Chapters 2, 4, 6 and 8.

Chapter 1.

The effects of task demands and cognitive resources on the information acquisition process in decision making: Literature review

1.0 Introduction

The first chapter of this thesis will begin by covering both classic and emerging models of decision making. Factors that precipitated the shift from classic normative theories to the newer descriptive models will be examined in Sections 1.1 – 1.3. Section 1.4 will explore the strengths and weaknesses of the human decision making system in terms of the trade-off between effort and accuracy. It is argued that this trade-off is necessitated by the fact that humans have limited information processing capacities, and is operationalised by the creation of a wide range of decision strategies available to the decision maker. This selection of strategies is termed the adaptive toolbox. Section 1.5 will examine the properties of the decision strategies that constitute the adaptive toolbox, before the most well-established strategies will be outlined in terms of their theoretical nature in Section 1.6 (how they can be identified experimentally will be outlined in Chapter 2). Section 1.7 will introduce the tripartite model of decision making, which is based on categorisation of all of the factors that could affect decision making into three groups: external factors (relating to the decision environment); internal factors (relating to the decision maker themselves); and decision factors (relating directly to the nature of the decision). Section 1.7 will then proceed to provide an illustration of some key factors from each branch of the tripartite model, each of which provides challenges for the decision maker. This illustration will serve to provide a solid basis for understanding the challenges that face decision makers, before the three key factors of interest to this thesis are introduced in their respective chapters. This introductory chapter will conclude with a summary in Section 1.8.

1.1 Normative decision theories

Arguably, the first 20 years of decision research focused on the quality of the decision made; i.e. on decision outcomes rather than the processes underlying decision making.

While modern theories of decision tend to be descriptive, classical decision theories were normative, or prescriptive, theories: in other words they focused on ideal performance (making a 'good' decision) under ideal conditions, were concerned with identifying the best decision to take, and assumed an ideal decision maker who is fully informed and able to compute with perfect accuracy. In addition, they were rooted in the concept of rationality, which assumes that people optimize decision outcomes. Rational decision making "has to do with selecting ways of thinking and acting to serve your ends or goals or moral imperatives, whatever they may be, as well as the environment permits" (von Winterfeldt & Edwards, 1986a, p.2). Rationality also implies a comprehensive gathering of all information relating to a decision, weighing up evidence that supports a decision alternative as well as all of the evidence that does not.

A classic, prescriptive rational model of decision making is Expected Value Theory (EVT), which is deeply rooted in classical economics. EVT states that people will select the decision alternative with the highest monetary value, derived from the multiplication of the possible monetary gain (x_1) and the probability of the outcome associated with that alternative (p_1):

$$EV = \sum_i p_i \times x_i$$

However, this theory is very limited in describing human decision making behaviour. For example, it cannot explain gambling, where the expected value of playing is less than the expected value of not playing. EVT fails because decision makers place subjective values on decision outcomes, and the value of a decision cannot always be determined in terms of financial reward. It is easy to see how the notion of subjective value leads to the violation of EVT. For example, a decision maker is faced with two alternatives: a higher probability of obtaining a lower amount of money vs. a lower probability of a receiving a higher monetary reward. EVT would predict that all decision makers would consistently select the latter, which has a higher expected value. However, if, for example, a decision maker only needs a certain amount of money to achieve a goal, and any extra financial reward is redundant, they may opt for the higher probability of winning a lower sum, if that lower sum fulfils their goal.

Another normative theory of decision making, evolved from EVT, is Expected Utility Theory (EUT; Von Neumann & Morgenstern, 1944), where the notion of utility relates to personal value (u1) rather than economic value:

$$EU = \sum p_1 \times u_1.$$

The concept of utility in EUT is likened to concepts of happiness, satisfaction, or fulfilling the goals of the decision maker.

A more complex version of EUT is Multi-Attribute Utility Theory (MAUT), which allows for the fact that a decision maker may often have multiple goals that they seek to achieve in any one decision (see Edwards, 1986; Galotti, 1999; Galotti & Kozberg, 1987). MAUT is another prescriptive theory, but one that acknowledges additional complexity in decision making, in recognizing that the decision maker may have multiple goals to achieve by any one decision. MAUT attempts to integrate the multiple decision goals of the decision maker with the variety of dimensions, or attributes, that relate to each one. Subjective weight judgements are assigned to each decision or attribute, which usually relate to specific goals. Each decision alternative is ranked along these weighted attributes, and the one with the highest overall value, or in other words, the decision alternative that achieves the most goals, is selected. MAUT does not consider probabilities of outcome. That is, it assumes that attributes are associated with the decision alternatives, and that there is no ambiguity or conditionality about the attribute or alternatives in the problem. It is also quite cognitively demanding, in that each alternative must be considered and ranked. It is a description of what should be done rather than what is done, and hence is a normative model. However, while it extends the concept of utility, it also begins to bridge the gap between normative and descriptive decision making, in that it starts to outline a more complex strategy underlying decision making rather than just an idealised approach.

Because EUT introduces the element of subjective value of decision outcomes (and starts to consider decision complexity in terms of competing goals), it begins to move away from pure normative theory, in that sometimes a maximization of expected utility will not be the greatest financial reward, as predicted by EVT. However, it continues to predict that human decision makers behave rationally, particularly in terms of consistency. Regardless of the value of a choice being judged purely financially, as in EVT, or in terms of psychological value, as in EUT, both theories rest on the fact that choice preference within a decision should be consistent. In other words, when an individual selects their preferred choice, this choice should always remain the preferred choice in that choice set regardless of how the choice set is presented. However, there are too many violations of these rational predictions for EUT to be considered an adequate descriptive theory.

1.2 Challenges to normative decision theories

The normative focus on decision making that developed from the economic perspective soon proved to be inadequate for explanations of real-life decision making. The most famous examples of the difficulties that the normative models as a whole are unable to account for include the Allais paradox, preference reversals, framing, and context effects.

1.2.1 The Allais paradox

An axiom of EUT is independence. Independence means that if a decision maker is indifferent between simple lotteries L_1 and L_2, they are also indifferent between L_1 mixed with an arbitrary simple lottery L_3 with probability p and L_2 mixed with L_3 with the same probability p. The value of L_3 should not influence the final choice; a rational choice between two alternatives should be made only on the differences between the two alternatives. The Allais paradox (Allais, 1953) proposes a pair of hypothetical decisions, such as the following Lottery A and Lottery B. They are presented separately, and people are asked to choose one option from Lottery A, and one from Lottery B:

- Lottery A1 – a 1.00 probability, or sure win, of winning £1 million
- Lottery A2 – a .10 probability of winning £5 million, a .89 probability of winning £1 million, and .01 probability of winning £0.

Generally people prefer Lottery A1 to Lottery A2. This already violates EVT, as the EV of A1 is less than the EV of A2. This is a demonstration of the certainty effect, that decision makers often prefer sure gains to any potential losses.

- Lottery B1 - a .11 probability of winning £1 million, and a .89 probability of winning £0
- Lottery B2 - a .10 probability of winning £5 million, and a .90 probability of winning £0.

Most people choose lotteries A1 and B2, but this is inconsistent with expected utility. First, essentially both gambles give the same outcome 89% of the time (£1 million for Lottery 1, and zero for Lottery 2), so, in expected utility, these equal outcomes should have no effect on the desirability of the gamble. If the .89 'common consequence' is disregarded, both gambles offer the same choice; a .10 probability of getting £5 million and .01 probability of getting nothing against an .11 chance of winning £1 million. Hence, the choice should be consistent across lotteries. This is an example of the violation of independence: the third outcome, the common outcome, is removed, but its removal alters the choice.

1.2.2 Preference reversal

The phenomenon known as preference reversal violates the axiom of transitivity in EUT (Slovic & Lichtenstein, 1968). The transitivity axiom states that if option A is valued more than option B, option A, and B is valued more than option C, A should be selected over C whenever these are compared (if A > B, and B > C, then A > C). However, research indicates that this is not always the case. The standard scenario for demonstrating preference reversal is as follows:

The decision maker is presented with 2 bets;

- P-bet: outcomes P_1, P_2, with probabilities p, (1-p)
- £-bet: outcomes $£_1$, $£_2$, with probabilities q, (1-q).

P_1 and $£_1$ are based on large value rewards, and the P_2 and $£_2$ values are small value rewards, or even losses. The important characteristic of this example is that p > q (the P-bet has higher probability of a large outcome) and that $£_1 > P_1$ (the £- bet has a higher possible large outcome). Thus, the labelling of the bets reflects that decision makers who select the P-bet have a relatively higher probability of a relatively lower gain, whilst if they select the £-bet they have a relatively smaller probability of a relatively higher gain. An example of this with monetary values follows:

- P-bet: £30 with 90% probability, and zero otherwise
- £-bet: £100 with 30% probability and zero otherwise.

A common experimental technique of measuring expected utility in the field of decision making is to see how much value the decision maker places on their choices by examining how much they would sell them for, or how much they would pay to have the opportunity to make a choice. Lichtenstein and Slovic (1971, 1973, and others since, e.g. Grether & Plott, 1979) have presented experimental evidence that people tend to *choose* the P-bet over the £-bet, and yet are willing to *sell* their right to play a P-bet for *less* than their right to play a £-bet. This can be restated in the context of risk-aversion: namely, although when directly asked, they would *choose* the P-bet, they are willing to accept a *lower* certainty-equivalent amount of money for a P-bet than they are for a £-bet, e.g. for the above example, their minimum selling prices would be £25 for the P-bet and £27, or so, for the £-bet.

Many have claimed that this violates the transitivity axiom (e.g. Loomes & Sudgen, 1983; Fishburn, 1985). The decision maker should value the choice they have selected equally by choosing it or by selling it; since it is assumed the decision maker selects the choice of the highest value. Selling the unselected choice (or paying for the right to have the choice) for a greater monetary amount than the selected choice violates the consistent nature of choice as predicted by EUT. Other researchers have conducted similar research with 'real-life' scenarios (for example, selecting a holiday destination, Shafir, 1993), and have found choices to be inconsistent; but in this case, the same decision was presented to the decision maker in slightly different ways. This evidence of 'framing' effects is another demonstration of the irrational nature of human decision making.

1.2.3 Framing

Framing refers specifically to the fact that changing the presentation of a decision can lead to different alternative choices being made, even when both the decision and choices are essentially consistent. One of the most famous examples of this was presented by Tversky and Kahneman (1974), in which participants were told that there will soon be an outbreak of a certain disease, and they have a choice between two programs to minimize casualties. They were then presented with two sets of two programs (A and B, or C and D), and asked to choose one program from each set. The programs presented in each set were equivalent across sets, so A is equivalent to C and B is equivalent to D in terms of lives saved/lost. However, in the first set, one program (A) is worded in terms of certainty of lives saved, and in the second set (C) in terms of lives lost. Programs (B) and (D) are worded in terms of probabilities of outcomes, the first stressing the number of people who will be saved, the second stressing the numbers who will be lost. So rationally, and according to utility theories, if a decision maker prefers A, they should also prefer C, and the same with B and D. However, research demonstrates consistently that people prefer A over B, and D over C. This preference reversal violates the axiom of transitivity.

1.2.4 Context effects

Perhaps the last, and best example of violations of utility theories of decision making is context effects. Context effects relate to the fact that when two identical alternatives are presented (A and B) twice, each time in the presence of a third alternative (C or D) which varies across presentations by how closely it is related in terms of choice dimensions to A or B, the proximity of the third alternative will affect the selection of either A or B. Note that C and D are poorer than the alternative they are nearest to in both contexts, making them unlikely ever to be selected. Thus, they should not affect the decision maker's preference for A or B.

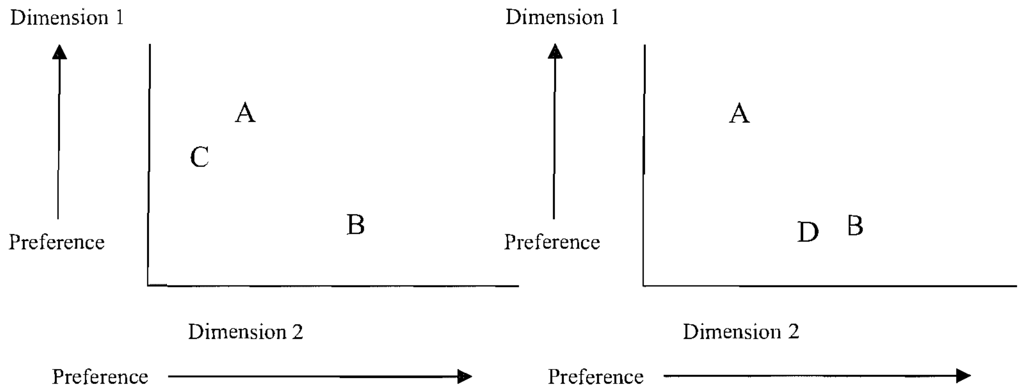

Figure 1.1 Context effects on alternative selection: two alternatives, A and B, are identical across contexts. The third alternative, C or D, varies across contexts in proximity to A or B.

However, research indicates that decision makers consistently prefer alternative A to B in Context 1, but B to A in Context 2 (Huber, Payne, & Puto, 1982; Simonson & Tversky, 1992). This tendency to shift selection to the choice with a similar, but inferior, alternative is called the attraction effect, and is a clear violation of the consistency of choice value proposed by the utility theories of decision making, as well as the constant ratio model (CRM) proposed by Luce (1959). This concept will be further explored in Section 1.7.3.2, which explores how the similarity of decision alternatives affects decision outcome.

1.2.5 Section summary

Normative models of decision making, such as EVT and EUT, make the fundamental assumption that decision makers are rational, and will make rational (and hence consistent) decisions. However, decision makers are not rational. They are vulnerable to a variety of influences that alter how the decision space and the decision alternatives in that space are perceived. Framing and context effects have already been mentioned, but these relate more to external factors of how the decision is presented, that are independent of the decision maker.

Decision makers do not make decisions in a vacuum; they take a very active role in determining how a decision is perceived. This is primarily due to the fact that decision makers have limited cognitive resources and must employ tactics such as selective attention, and a range of heuristics to cope with the cognitive demands around them. Before the implications of the limitations of the human cognitive system are discussed, some of the descriptive models of decision making that emerged from the challenges to the assumption of human rationality held by the normative decision models will be briefly considered.

1.3 Descriptive decision models

Clear violations of the normative criteria of consistency were apparent, and this pre-empted a shift from a focus on normative models to descriptive models of decision making, which attempt to describe what people actually do when making decisions. Normative models were recognised to be of limited use, when research findings were making it increasingly obvious that humans are not rational beings. Instead, they operate under 'bounded rationality' (Simon, 1956), which acknowledges that humans are cognitively limited, and are also influenced by other factors such as emotion. Simon (1956, p. 130) states that "boundedly rational agents experience limits in formulating and solving complex problems and in processing (receiving, storing, retrieving, transmitting) information." As a result, humans do not make perfect decisions all the time; rather, they make decent decisions most of the time. It is worth noting that bounded rationality accounts for the fact that some techniques associated with irrationality, such as random choice, are sometimes the best approaches to take. The focus of descriptive models on what actually happens in decision making, and on the decision maker as an individual, shifted the study of decision making from placing primary importance on the decision outcome to an emphasis on the processes underlying decision making.

The challenge for descriptive models of decision making is to account for the irrational tendencies exhibited by decision makers, such as the Allais paradox and preference reversal.

1.3.1 Prospect theory and Regret theory

One of the major descriptive models of decision making under conditions of risk and uncertainty is Prospect theory (Kahneman & Tversky, 1979b), which developed from EVT, but was modified to account for non-normative decision behaviour. Prospect theory is rooted in two primary assumptions: first, that utilities, or 'values,' are evaluated subjectively, with respect to a reference point determined by the decision maker. This assumption accounts for the inconsistencies caused by framing effects: how a decision is framed affects the reference point by which the utilities relating to that decision are weighted. For example, if a decision is framed so that it emphasizes the positive aspects of what the decision maker currently has, they will be less likely to take risks. Similarly, if a decision is framed such that what may be lost is emphasized, decisions makers will be more likely to take risks to avoid or minimize loss.

The second assumption of Prospect theory is that these subjective utilities are multiplied by weights, or probabilities, that are also subjective, not objective as stated by EUT. This subjective 'psychological probability,' is referred to as the π function. According to this function, very low and very high probabilities are weighted subjectively more heavily than intermediate probabilities. This is due to the fact that decision makers 'over-value' certainty and, in general, are loss-averse in the context of risky decisions. In other words, potential losses loom greater than equivalent potential gains (see Figure 1.2). In addition, people tend to be risk-seeking when faced with the prospect of losses, but risk-averse when faced with the prospect of gains, which leads to different subjective weighting of probabilities (Kahneman & Tversky, 1979b).

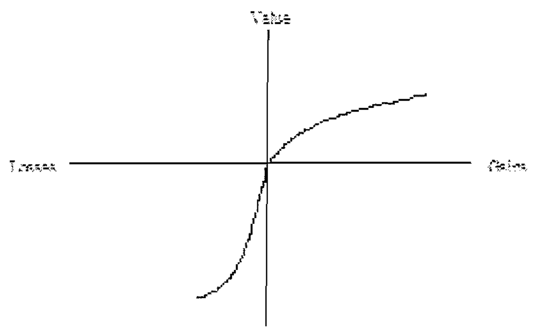

Figure 1.2: A hypothetical value function according to Prospect theory (Kahneman & Tversky, 1979b)

The fact that subjective probabilities are not simply numerically additive can account for the Allais paradox, in that the π value associated with a probability of 1.00 (certainty) is greater than the sum of the π value of .11 plus the π value of .89. It can also eliminate the problem of preference reversal, since it allows the decision maker to assign a personal value to an outcome rather than an objective value, which may not be strong enough to maintain consistency (Plous, 1993).

Recently, there have been suggestions that Prospect theory is not comprehensive enough to account for decision making across a range of scenarios. Brandstatter and Gussmack (2007) demonstrated that Prospect theory cannot account for the fact that, in comparing gambling versus knowledge-based decisions, people prefer a knowledge bet over the sure gain if the probability of winning is high. This is in contrast to Prospect theory, which predicts the opposite.

The subjective value of a decision alternative may also include possible emotional outcomes related to the result of selecting that alternative. Another descriptive theory of decision making, Regret theory, stresses the role of psychological outcomes of decisions in influencing outcome preferences. Regret theory suggests that humans overweight anticipated feelings of regret when the difference between outcomes is large (Bell, 1982; Loomes & Sugden, 1982). This would account for the Allais paradox, in that one of the reasons for preferring the certainty provided by the 1.00 probability of winning £1000 to the option where the probability of winning £1000 is .89, the probability of winning £5000 is .10, and the probability of winning £0 is .01 would be the possibility that if the latter were selected, there is a chance the decision maker would not win any money. The regret associated with that prospect may be prohibitive for the selection of that option (Hoelzl & Loewenstein, 2005; Wright & Ayton, 2005; van Dijk & Zeelenberg, 2005).

1.3.2 Section summary

The first changes in the theoretical move from normative to descriptive models of decision making were described above. The critical difference which accounted for the shift between the two was the recognition that human decision making is not ideal, or normative, and that humans are not purely rational. Even more recent descriptive models of decision making, such as Sequential Sampling and Decision Field Theory (Dror, Busemeyer, & Basola, 1999; Roe, Busemeyer, & Townsend, 2001), have undergone several further changes; first, they have become increasingly mathematical in nature. Second, and in a very positive step, they have begun to draw on a solid foundation of cognitive psychological theory, rather than the previous attempts based on the modification of economic frameworks. These models range from simple decision strategies, which will be discussed in detail in Section 1.7, to more complicated models such as Sequential Sampling and connectionist models, which are beyond the scope of this thesis. Third, these new models focus on 'boundedly rational' decision makers, and assume that humans are not ideal decision makers. Fourth, the newer models account for a much more dynamic decision process, where the decision maker is more oriented to different choices at different points in time. As well as proving very effective in the domains of perception, memory, and categorisation (Dror, Busemeyer, & Basola, 1999), models such as those mentioned above have proved effective in accounting for certain paradoxical findings in the decision literature such as the similarity effect (Tversky, 1972), the attraction effect (Huber, Payne, & Puto, 1982), and the compromise effect (Simonson, 1989). These new models will not be discussed in great detail, as they do not address the research questions of this thesis. They are more representative of a general framework for how a decision is achieved and at what point an option is selected, rather than a detailed focus on the information acquisition underlying the decision process, which is the focus of this thesis.

Before discussing the decision strategies underlying information acquisition, this chapter will next focus on the theoretical constructs relating to human cognition which can assist in the understanding of why human decision makers are only boundedly rational: limited cognitive resources and cognitive adaptability. Once these concepts have been considered, their relevance to the process of information acquisition in decision making should be apparent.

1.4 Cognitive limitations: The effort/accuracy trade-off and the adaptive decision maker

The comparison between normative and descriptive models highlights a fundamental issue that is a key topic in the study of decision making, which also transcends cognitive psychology in general: the trade-off between the amount of effort devoted to, and accuracy achieved, on almost any task. This trade-off is rooted in the fact that human cognitive resources, or the amount of mental energy available for any given task, are limited (Kahneman, 1973; Marschak, 1968; Miller, 1956; Navon & Gopher, 1979; Park & Schwartz, 2000; Thomas, 1983). In a world where a human must function on a variety of cognitive levels, and is bombarded with a myriad of stimuli through all of the senses, these limited resources are in demand from a number of competing tasks. It is simply not possible to devote the ideal amount of cognitive resources to every competing cognitive interest; the individual would be unable to cope with such demands and could not function. Simon (1956) highlighted this point early on in the study of decision making, as he believed that it is the limits on cognitive resources that make us boundedly, rather than purely, rational.

One of the key elements to the cognitive success of humans in attaining higher cortical functioning is the ability to focus attention only on relevant tasks, and even then to streamline the process of dealing with those tasks. This takes many forms and results in different by-products across different areas of cognition (for example, visual illusions in perception (Gregory, 1997), chunking in working memory tasks (Miller, 1956), stereotyping in social judgement (Macrae, Hewstone, & Griffiths, 1993), attentional control (Kahneman, 1973; Sperling, 1960; Wickens, 1984)), but in decision making this streamlining process rests on the use of certain specialised heuristics. These heuristics will be described later in detail, but at this point it is necessary simply to introduce the idea that the majority of, if not all, decision researchers recognise that decision makers have a range of strategies that they can apply to assist them in the decision making process. The reason for the adoption of many strategies is to minimize the amount of cognitive effort used, while maximising decision accuracy. Traditional cost-benefit frameworks and, more recently, the Effort-Accuracy framework proposed by Payne *et al.* (1993), are based on this premise, and the latter will be discussed in detail.

1.4.1 The adaptive toolbox

Once the notion of bounded rationality emerged, and descriptive models of decision making along with it, it became apparent that strategies of decision making that appeared highly irrational are actually very successful strategies, and as such may be considered rational. An example of this seemingly irrational, rational behaviour is 'one reason' decision making. As the name suggests, this is decision making on the basis of a single criterion. Researchers argued that if simple decision strategies could outperform rational models, and do so while expending less cognitive effort, it was far more rational for the decision maker to employ these strategies than the supposedly rational, normative ones (Czerlinski, Gigerenzer, & Goldstein, 1999; Gigerenzer & Goldstein, 1996; Gigerenzer & Selten, 2001). In other words, the route to the best decision performance is not always through using computationally demanding normative strategies, but cognitively-efficient ones which lead to the best overall performance in terms of accuracy achieved for the amount of effort spent. In other words, people select strategies adaptively depending on characteristics of the situation (Rieskamp & Hoffrage, 2008). Gigerenzer and his colleagues suggested a range of heuristics called 'fast and frugal' which were designed to solve a variety of decision problems based on a very small proportion of the information available (Gigerenzer, Todd, & the ABC Research Group, 1999). Along with Beach and Mitchell (1978), who originally proposed the cost-benefit framework in decision making, and Payne *et al.* (1993), Gigerenzer *et al.* (1999) conceptualise the mind as an '*adaptive toolbox*' that is equipped with a multitude of different heuristics tailored to handle specific problems and decision situations. Humans are thought to react adaptively, in that they select the appropriate heuristic contingent on task demands. Exactly which strategies are selected in the face of different task demands is a rich area of study, and is one espoused by Gigerenzer and the notion of the adaptive tool box. Essentially, the study of the adaptive toolbox is descriptive, in that it analyzes the selection and structure of heuristics in different environments, both social and physical The study of ecological rationality, as Gigerenzer puts it, is prescriptive and identifies the structure of environments in which specific heuristics either succeed or fail (Gigerenzer, 2008). Some of these decision environment factors and their effects on the decision making process form the core of this thesis.

The fact that decision making is contingent on task demands, and that this contingency is rooted in the availability of different decision making tools, is critical. This implies that decision making is flexible and that decision makers are aware of the effort-accuracy trade-off; certainly both the traditional cost-benefit frameworks and the Effort-Accuracy framework propose this to be the case. It is true that some models (in particular perceptual models such as Prospect theory, Kahneman & Tversky, 1979) do not propose that the decision maker is actively selecting decision heuristics; some research based traditional cost-benefit frameworks supports this idea that decision makers are only limitedly aware of effort-accuracy trade-offs (Fennema & Kleinmuntz, 1995). However, recent research indicates that decision makers are aware of the effort-accuracy differentials provided to them by different strategies and are good at selecting a strategy to fit the task (Chu & Spiers, 2004); although their perceptions of effort-accuracy may sometimes be biased (Payne *et al.*, 1993). This awareness of task-dependent, optimal strategy selection is important for topics such as learning, training, and improving decision making abilities. One must be aware of different strategies and where they are best applied to optimise decision making. The majority of decision making researchers believe that decision makers are aware of the potential for adaptivity, which enables the latter to tailor their decision making process by adopting different strategies to optimize decision outcome within the limits of the decision task and context. The concepts of adaptability and contingent decision making are strongly related to the dominant theoretical framework of how decision makers select which decision strategy to adopt in any particular decision task: the Effort-Accuracy framework (Payne *et al.*, 1993).

1.4.2 The Effort-Accuracy framework

This section will focus largely on the theoretical nature of this framework, proposed over the years by John Payne in conjunction with different researchers, but formally described by Payne, Bettman, & Johnson (1993). The exact means by which effort is operationalised and measured in the context of decision strategies will be examined in Section 1.6. This chapter will not focus in any detail, beyond a basic definition, on the operationalisation of accuracy, as this is a complicated concept in its own right and is not central to this particular thesis.

All cognitive frameworks involving trade-offs centre on a core theme: the trade off between the costs incurred and benefits accrued by employing that framework. In the Effort-Accuracy framework (E-Af; Payne *et al.*, 1993), the cost relates specifically to cognitive effort and the benefit refers specifically to decision accuracy. Each decision represents a particular balance between task demand and the computational availability of the decision maker; in other words, each decision represents a different point along the on effort-accuracy continuum (see Figure 1.3).

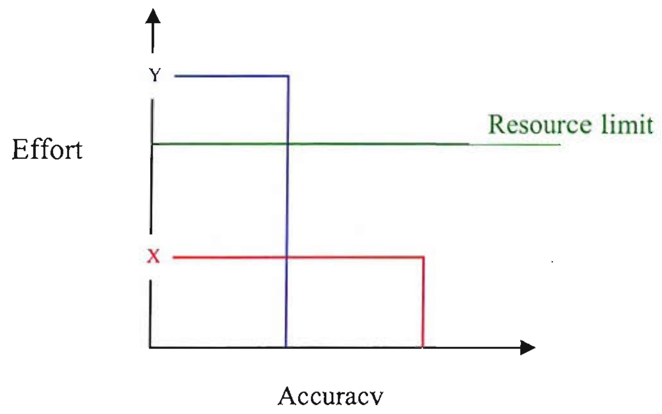

Figure 1.3 An illustration of the effort-accuracy continuum, with a low demand decision (X) and a high demand decision (Y)

Figure 1.3 represents an effort-accuracy continuum depicting two decisions: X and Y. The task demand of the decisions is represented by the height of the letter representing that decision. The decision maker has a fixed amount of cognitive resources that they cannot exceed (a resource limit), represented by the green horizontal line. This will be higher for a cognitively-enhanced population, and lower for a population with diminished resources. For each decision maker, this resource limit will also vary, depending on competing demands on attention and working memory. The difference between demand and resources determine what strategy the decision maker will choose (represented by the vertical and horizontal lines connecting the effort and accuracy axes), and hence, what level of accuracy the decision maker is predicted to achieve.

The E-Af would predict that any population will adopt more economical strategies as demand increases, particularly as effort begins to be exceeded by demand. The E-Af is based on five major assumptions: first, as discussed above, the decision maker has a certain number of strategies and heuristics available to employ in solving decisions of varying complexity: the adaptive toolbox. Exactly what strategies are generally found in this toolbox and reasons why they may be included are discussed later in this chapter.

The second assumption is that the strategies in the adaptive toolbox are assumed to have differing disadvantages (costs) and advantages (benefits), in relation to the decision maker's desired outcome and the specific constraints of any decision task. In this framework, as mentioned previously, the costs are operationalised in terms of cognitive effort required, and the benefits in terms of decision accuracy. This assumption implies that the structure of any decision task can determine the likelihood of certain strategies leading to a 'good' decision outcome.

The third assumption is strongly linked to the second, namely that strategies have different costs and benefits associated with them, but that these change across different decision environments. In other words, different decision tasks will lead to certain strategies that have relative advantages and disadvantages over others for that particular task. Overall, some strategies that appear attractive in terms of decision outcome in some situations will not appear so in others, and some strategies that appear unattractive in terms of decision outcome in some situations, again, will not appear so in others.

Fourth, it is assumed that the decision maker actively selects the strategy or strategies that appear to best suit the decision task, according to their best judgement. This subjective perception of costs and benefits, in this case effort and accuracy, has been discussed above in this section, and overall it is reasonable to assume decision makers are aware of such trade-offs, as a result of experience (Chu & Spiers, 2004).

Fifth, and finally, is the assumption that decision strategy selection is, to some extent, predetermined by the decision maker's current state. Specifically, decision makers' prior experience with similar and other decision tasks, as well as other factors such as mood, expectations, and knowledge of the decision area, influence the selection of decision strategies before the specific decision task is thoroughly considered. In other words, a priori perceptions of the current task and decision strategies in general influence which strategies will be selected, rather than an effortful, bottom-up, diagnostic of the decision task. This does not discount the notion that opportunistic strategy selection, or even on-the-spot strategy formation, does not occur, but as the decision maker becomes more experienced, this bottom-up strategy development and use is less likely to occur (Hayes-Roth & Hayes-Roth, 1979).

The concept of strategy selection as a mechanism to balance the effort-accuracy demands of a decision is not unique to Payne *et al*; in fact, it is the most frequently invoked explanation for contingent strategy use in decision making (Beach & Mitchell, 1978; Johnson & Payne, 1985; Klayman, 1983; Russo & Dosher, 1983; Shugan, 1980). A further examination of how operationally to define and measure cognitive effort will be undertaken in Section 1.6.11, after the dominant, universal decision strategies in the adaptive toolbox are discussed. This review will illustrate the differences in effort and costs between them.

1.4.3 Section summary

One of the reasons that normative models of decision making are inadequate is that they illustrate an ideal situation, in which all of the individual's cognitive resources are available to be applied to the current decision task. As outlined above, this simply does not, even cannot, happen. Certainly, particular factors can influence how much cognitive energy is applied to the decision task (and these will be discussed later in the chapter), but it is rare that all of an individual's cognitive resources will be applied to a single decision task. The common discrepancy between task demands and cognitive resources, or computational availability, leads to the use of decision heuristics, or cognitive shortcuts, which emerge as integral tools in real world decision making. Decision heuristics take the form of specific decision strategies, which relate to the process of information acquisition in the decision. The general properties of these decision strategies will be discussed in the next section, followed by a discussion in Section 1.6 about specific decision strategies that are well-established in the literature.

1.5 Decision strategies: General properties

The concept of the adaptive decision maker is based on the idea that decision making is contingent on a variety of factors (which will be examined in detail in Section 1.7). The decision maker adopts different strategies for different decisions to optimise accuracy with the cognitive resources available. Each decision strategy can be thought of as a method (or a sequence of operations) for searching through the decision space (information provided by the alternatives and attributes available) (Payne *et al.*, 1993). This section focuses on the general properties of the most established decision strategies that have been identified, while the next section will focus on each of these strategies in detail. All of the heuristics that have been selected for examination in this thesis have been selected as they were considered to be the most common and the best researched of all the strategies in the literature.

1.5.1 Compensatory vs. Non-compensatory

The central distinction between compensatory and non-compensatory strategies is how they deal with conflict between decision attributes in terms of value. Some attributes of a particular alternative may have very high values and be very attractive, while others may have low values and be unattractive. Deciding on that alternative, then, involves taking 'the good with the bad,' and implies that a high value of one attribute can make up for, or compensate for, poor values of other attributes. Decision strategies where such tradeoffs in value can occur are called compensatory strategies. Strategies that do not make such tradeoffs are called non-compensatory. The critical issue for non-compensatory strategies is the prioritization of attributes; in a classic non-compensatory strategy, a poor value on a key attribute will ensure that alternative is never selected, regardless of how highly valued other attributes in that alternative are. In other words, a decision rule is non-compensatory when a decision, determined by some attributes of an object, cannot be reversed by other attributes of the object (Dillon, 1998; Schoemaker, 1980). For classic, compensatory strategies, good values on one attribute can offset bad values on another, as the alternative is judged as a whole and attributes are not ranked within it. Some strategies are partially compensatory, in that the total number of advantages for an alternative matters, but the relative sizes of the advantages do not (Payne *et al.*, 1993). Judging alternatives more holistically, as compensatory strategies do, is also linked to the cognitive costs incurred by these strategies.

Compensatory strategies are more cognitively demanding that non-compensatory strategies. First, they require integration of all the decision attributes in an alternative to obtain an overall alternative value. This complete integration and consideration of the entire decision space is cognitively effortful. Second, the trade-offs on which compensatory strategies are based involve conflict. Making explicit attribute value tradeoffs is emotionally difficult for most people, as certain attribute values may be compromised in the trade-off process, and this difficulty adds to the cognitive demands of the task (Hogarth, 1987). Generally, and throughout this thesis, the term non-compensatory is used to denote a cognitively-economical strategy.

1.5.2 Amount of processing

The amount of processing required to evaluate any decision space is synonymous with the cognitive demands of that decision. Processing involves the identification, evaluation, and integration of decision information. This is contingent on two main factors. First, decision size is important, as the larger the decision space (more attributes and/or alternatives), the more information there is to process. Second, the ease with which information is identified, evaluated, and integrated affects the amount of processing required; if there are a number of distractions and processing is impoverished as a result, it will require more effort to revisit the information and process it properly. Similarly, the ease with which the information provided in the decision space can be processed will affect how much processing is required. If the information is presented in a complex or ambiguous form, processing demands will be greater. As such, amount of processing relates to both the quantitative information about the items considered (how many, for how long), as well as qualitative information (the depth of processing, which may occur outside of information acquisition).

A key distinction between decision strategies is how much information they require to be processed (Payne *et al.*, 1993). Some strategies reduce the amount of information to be processed by explicitly ignoring information in the decision space; information that is potentially relevant and might improve decision accuracy. This is an example of an effort-accuracy trade-off. In other strategies, individuals process all the information available to them. What information should be ignored is determined by different mechanisms, including the prioritization of attributes and the particular values of the alternatives and mental cut-offs, or threshold, for that decision. This will be elaborated upon when the individual strategies are outlined in Section 1.6.

1.5.3 Consistent vs. selective processing

It is possible to make a decision without evaluating any attributes (random choice), or by just evaluating one (satisficing). However, established decision strategies demonstrate that, except in cases of random choice or satisficing, normally at least 2+ pieces of information are processed in any decision space. Another critical difference between decision strategies is the extent to which processing across information items is consistent, or selective. Consistent processing implies that an equal amount of processing is spread evenly across all attributes and alternatives examined. Selective processing is more variable: some items will be processed for a much longer time than others, some may not be processed at all. Research has consistently suggested that consistent processing is more indicative of compensatory decision strategies (Payne, 1976). For each item of information to be systematically (and this implies consistently) processed, the strategy must be compensatory; although consistent processing is not confined to decisions in which each piece of information is examined. By definition, non-compensatory strategies are based on selective processing, as not all of the information in the decision space is examined.

1.5.4 Alternative-based vs. attribute-based processing

Another key property of decision strategies is whether the processing of the decision alternatives in the decision space is attribute or alternative-driven. Alternative-based processing, often termed holistic processing, is completed across attributes, within each alternative. In other words, a certain number of attribute values belonging to a particular alternative are examined before any information from a second alternative is considered. Attribute-based processing cuts across alternatives, the values for a particular attribute are examined for a number of alternatives, before any information from another attribute is examined. It is suggested that holistic, alternative-based processing is more cognitively effortful than attribute-based processing (Russo & Dosher, 1983); this is likely to be due to the fact that the attribute information for each alternative is integrated to form a total value or weight for that alternative, and each of these weights must then be retained for comparison across alternatives. An alternative-driven search is also termed interdimensional as it cuts across the dimensions or attributes, while an attribute-driven search is termed intradimensional.

1.5.5 Formation of evaluations

The reason that alternative-based processing is more cognitively demanding than attribute-based processing is related to the formation of evaluations across alternatives. Some strategies involve the determination of an overall evaluation (value or score) for each alternative considered, particularly the compensatory strategies. Other (non-compensatory) strategies eliminate and select alternatives without ever calculating an overall value.

1.5.6 Quantitative vs. qualitative reasoning

The last major aspect on which decision strategies vary is the type of reasoning underlying their process. This distinction is somewhat vague, but has been explored in several ways (Hegarty, Just, & Morrison, 1988; Tversky, Sattath, & Slovic, 1988). Quantitative reasoning is thought to be more 'mathematical,' for example, strategies involve the summing of attribute values across alternatives (some of the more complicated ones obtain these values by multiplying initial values by subjective weights), or involve frequency counts. Some of the strategies involve reasoning that is not so calculated (e.g. elimination-by-aspects (Tversky, 1972), or satisficing (Simon, 1955)), where values or attributes are compared, but their difference is determined more by a subjective, qualitative judgement of their difference.

1.5.7 Section summary

The properties outlined here are those that are generally accepted in the literature: some are well-researched, others less so. These general properties of decision strategies are critical for the identification of each strategy: the unique combination of these properties defines each strategy (as seen in Table 1.2, Section 1.6). The next section of this chapter will explore the most well-established decision strategies in detail. It is these decision strategies that are the dependent variable of interest in all of the research outlined in this thesis, as this research program is interested in exploring how the selection of decision making strategies is influenced by factors such as time pressure, decision complexity, and amount of cognitive resources.

1.6 Decision strategies: In detail

Decision making is, by its very nature, contingent on a variety of factors which include the decision, the decision maker, and the decision environment. Contingency in decision making is defined by changes in the decision strategies, or ways of processing decision information, used to acquire information about the decision alternatives (Payne *et al.*, 1993). The main decision strategies that have currently been identified in the literature will be outlined in this section.

As outlined earlier, an individual's strategy repertoire, or adaptive toolbox (Gigerenzer *et al.*, 1999), is determined by a variety of factors, including experience, level of cognitive development, and more formal training. Different individuals do not employ the same strategies in equivalent decision tasks (Onken, Hastie, & Revell, 1985), although for an individual decision maker it is intuitive that strategies that have proved effective in past decision making tasks will be more likely to be used when similar decision tasks present themselves in the future. It is important to stress, however, that decision makers are not consistent across decision tasks (Beach, 1993), and previous experience only increases the likelihood that effective strategies will be recalled for use in new, but similar, tasks. It is also important to note that decision makers are not consistent in the strategies they use even within tasks: they may and do use compensatory and non-compensatory strategies at different stages of the same task (Payne, 1976; Payne, Bettman, & Luce, 1998). The more variety in the decisions that the decision maker makes, the more they will be likely to experience and develop new strategies to cope best with this range (Kruglanksi, 1989). In terms of cognitive development, it has been shown that children of 12 years of age know a good number of decision strategies, but employ them less consistently than do adults (Klayman, 1985). Formal training can also expand the decision strategy repertoire, as mnemonics can expand working memory capacity (Larrick, Nisbett, & Morgan, 1990). In addition, the frequency and recency of prior use of a particular strategy will influence its availability to the decision maker. Thus, each individual decision maker will have a unique decision strategy repertoire upon which s/he can draw when decision making, and each individual will be differentially effective and efficient across strategies.

Nonetheless, there are certain common decision strategies that could constitute the average adaptive toolbox, and these are outlined below. While this thesis does not focus on the explicit usage of these strategies, it is important to examine specific decision strategies to illustrate the range of compensatory and non-compensatory strategies available to a decision maker.

1.6.1 Weighted Additive Rule

The weighted additive rule (WADD: Payne, Bettman, & Johnson, 1988; Zackay & Wooler, 1984) is the most comprehensive decision strategy; it is a normative strategy that, for preferential choice decisions such as the ones dealt with in this thesis, assumes an ideal decision accuracy level of 1.0 (Keeney & Raiffa, 1976). In this strategy, reasoning is quantitative. The values of each alternative on all the relevant attributes are considered; in addition, the relative weights or importance of the attributes to the decision maker are also taken into account. An overall 'alternative value' is obtained for each alternative, which is determined by the multiplication of each attribute value by the subjective weight of that value and the summing of these modified, subjectively weighted attribute values within the alternative, resulting in an overall alternative value, or overall evaluation. WADD is a very computationally demanding strategy. In addition, because all relevant information is examined, this exhaustive strategy must deal with trade-offs between attribute values, and as such is a compensatory strategy. It is based on consistent processing and is high in processing demands, as each relevant piece of information is processed for a similar amount of time. WADD is also alternative-driven, or interdimensional, in nature. For decisions made under risk, the EVT, EUT, and prospect models outlined earlier are similar strategies, which deal with obtaining overall alternative values. WADD is an idealised decision making strategy, which is not frequently employed in real life. Situations in which it can be employed are those where the decision space is small and the decision maker's cognitive resources are ample to meet task demands. However, it represents a normative decision strategy that provides a maximum effort measure and a maximum relative accuracy measure, against which all other decision strategies can be compared.

A particular point of interest for researchers is the nature of the subjective weights of the attributes within the WADD framework. These weights are critical in WADD for the overall evaluation of decision alternatives. One aspect of interest is their consistency: are subjective values for certain attributes determined locally, in the context of that particular decision space, or are they more global, enduring tenets? There is some evidence for the former, in that the subjective weights vary relative to the range of attribute values across the alternatives in the decision space; the greater the range, the greater the importance of the attribute (Goldstein, 1990). Other evidence suggests that some attribute values, such as the importance of safety, are relatively consistent across different decisions, or choice sets (Beattie & Baron, 1991). Another, very quantitative debate, questions if weights influence attribute values by means of an adding or an averaging process. The additive model is based on simple summing and has no constraints, whilst the averaging model constrains the weight values to a total of 1 (see Stevenson, Busemeyer, & Naylor, 1990).

1.6.2 Equal Weights heuristic

The equal weights heuristic (EQW) is a simplified version of the WADD, in that all alternatives and all attribute values for each alternative are examined; as such it is very high in processing, is compensatory, and interdimensional. However, it is not as intensive in terms of processing as the WADD, as, similar to the MCD heuristic, it is a compensatory strategy that ignores the concept of attribute weights. EQW ignores both the relative importance and the probability of each attribute. Overall alternative values are determined simply by summing the 'raw' or 'objective' values of each attribute across the alternative. Critically, this assumes that attribute values are expressed, or can be understood, in terms of a common scale of reference. Several researchers have suggested that the EQW is a highly accurate simplification of a normative decision strategy, thus allowing reduced effort while retaining high levels of accuracy, and as such is a valuable tool at decision makers' disposal.

1.6.3 Additive Difference Model

The additive difference model (ADDIF; or linear compensatory model, Edwards & Tversky, 1967) is similar to the WADD model in its emphasis on subjective weights (and hence quantitative reasoning) and can appear similar from behavioural data alone. In this strategy, pairs of alternatives are compared directly on each attribute, and the differences of the subjective values of the two alternatives on that attribute are determined. The subjective weighting function is then applied to that difference value, and the weighted differences across all relevant attributes are summed together to form an overall evaluation of which alternative in the pair is more heavily weighted. This strategy is compensatory, and intradimensional, or attribute-driven in nature. It is based on consistent processing, and the amount of processing is high as no relevant information is ignored.

Other researchers have suggested variations of the ADDIF process, proposing that attribute differences are processed sequentially, and that the summed differences are accumulated until the sum total of attribute values of one alternative exceeds another by passing some subjectively determined criterion (Aschenbrenner, Bockenholt, Albert, & Schmalhofer, 1986). Furthermore, it has been suggested that this criterion is set at the point in the effort-accuracy trade-off that the decision maker is willing to accept (Bockenholt, Albert, Aschenbrenner, & Schmalhofer, 1991).

1.6.4 The Majority of Confirming Dimensions heuristic

The majority of confirming dimensions heuristic (MCD: Russo & Dosher, 1983) is essentially a simplified version of the ADDIF model. In this compensatory strategy, pairs of alternatives are processed by comparing attribute values for each attribute. The difference between attribute values for each comparison is judged in a qualitative way (this one is 'better' than the other, this one is 'worse'). The alternative with the highest number of 'winning' attributes is retained. This alternative is then compared against another by the same process, until a final comparison of the remaining two alternatives and an overall 'winner' is determined. MCD is simpler than the ADDIF strategy in that it does not use subjective weights. Additionally, the reasoning underlying the process is not only qualitative but binary; only the direction of the difference (better vs. worse) is recorded, not the magnitude of that difference. This strategy is intradimensional; processing is consistent across the information considered, but not all relevant information is examined.

1.6.5 The Frequency of Good and Bad Features heuristic

The last of the compensatory decision strategies that will be of interest to this thesis is the frequency of good and bad features heuristic (FRQ: Alba & Marmorstein, 1987). The reasoning underlying this strategy is quantitative, but very basic. Essentially, it is suggested that decision makers evaluate and select alternatives based on counts of the good/bad attribute values, or features, of the alternatives presented. The decision maker would need to determine subjective cut-offs, or thresholds, which would allow the classification of a value as good or bad, in order to implement this strategy. In an even simpler form, the decision maker may only consider the frequency of either good or bad attribute values, rather than a combination of the two. In this strategy information is ignored, so the processing demands are lower. However, processing remains consistent across relevant information, and this strategy is interdimensional in nature, as overall alternative evaluations are formed sequentially.

1.6.6 Random choice

Non-compensatory strategies imply less demand on cognitive resources by their very nature, and the most undemanding non-compensatory strategy is random choice (RAN). RAN involves, as the name suggests, randomly selecting an alternative without any processing of the information provided in the decision space. It is completely at the opposite end of the cognitive-effort spectrum to WADD, and thus provides a baseline of minimum effort and accuracy. While requiring minimal to no processing effort, accuracy levels (measured by choice quality) are variable.

1.6.6 Satisficing

The second most economical non-compensatory decision strategy, in terms of cognitive effort, is satisficing (SAT). This was the first decision strategy to be suggested in the literature (Simon, 1955). SAT is an interdimensional strategy, in which alternatives are considered one at a time in the order that they are presented to the decision maker. A cut-off value for each attribute in the decision space is determined by the decision maker: this is often termed the aspirational value. The alternatives are considered attribute by attribute, and as soon as one of their attribute values falls below the aspirational value, that alternative is discounted from the decision. The decision maker continues through the alternatives, and selects the first one whose attribute values meet and/or surpass the aspirational values for all of the attributes. No further alternatives will be considered, regardless of possible alternatives that may also exceed the aspirational values to an even greater extent (i.e. a better alternative). As such, decision makers satisfy themselves with the first alternative that meets their basic criteria. If none of the alternatives in the decision space satisfy the aspirational cut-off for all attributes, the apirational cut-offs will be lowered and the process repeated until an alternative is selected. Clearly, the order in which alternatives are presented to the individual is of critical importance when this heuristic is employed.

1.6.7 Elimination by Aspects

The elimination by aspects heuristic (EBA; Tversky, 1972) is a non-compensatory, strongly intradimensional strategy that begins by the determination of the most important attribute to the decision maker in any particular decision space. Tversky believed this key attribute is selected probabilistically: the probability that any attribute will be selected is a function of its subjective weight or importance to the decision maker. Once the key attribute has been selected, a cut-off value, or threshold value, is determined. All key attribute values are compared against the threshold value across all alternatives, and any alternatives that do not meet, or exceed, the threshold value are discounted. Then, the next key attribute, in other words the second most important, is determined, a threshold value for that attribute decided, and all alternatives that do not meet it discounted. This process, which is rooted in qualitative reasoning, is repeated through the third most important attribute, and so on, until one final alternative remains. EBA does not process all of the information available in the decision space, as only attributes that have been prioritised by the decision maker in terms of subjective importance are examined. In addition, it does not process the information considered consistently. However, EBA is at least a partially rational strategy in terms of the consideration of order of importance in the attribute.

1.6.8 Lexicographic heuristic

The lexicographic heuristic (LEX; Tversky, 1969) is another intradimensional, non-compensatory strategy, but is even less cognitively-effortful than EBA. Similar to EBA, LEX begins by the determination of the most important attribute to the decision maker, and all of the values across alternatives for this key attribute are considered. The alternative with the best value on the key attribute is selected, and the decision is made. If two key attribute values for two different alternatives are identical, the second most important attribute will be considered in the same manner, and so on, until there is a clear 'winner.' Overall evaluations of alternatives are not made, reasoning is qualitative, and the information is not considered consistently.

The concept of 'identical' key values has been extended to include the idea of just noticeable differences (JND), which refers to the fact that while values may not be identical they may still be close enough to be considered equal. If key values are within a JND across alternatives, they will be considered to be tied and the second most important attribute will be considered. This less strict version of LEX is called the semi-lexicographic (LEXSEMI) heuristic. While EBA is generally considered to be as boundedly rational a heuristic as decision makers will employ, LEX has often been cited for being irrational in that its usage may lead to intransitivities of preference, in other words X >Y, Y > Z, Z > X. However, arguments have been put forward that it is sometimes reasonable to violate transitivity, and the need for rational decisions, or rather boundedly rational ones, to include transitivity have been questioned (Fishburn, 1991).

1.6.9 Other heuristics

For repeated choice (identical decisions which present themselves again, at least once), several other heuristics have been outlined. When presented with an identical decision to one encountered previously, a decision maker may simply select the alternative that they selected last time without any evaluation of the decision space at all: this is called the habitual heuristic (see Payne *et al.*, 1993). Habitual heuristics may also be relevant in cases of expertise, where similar (albeit non-identical) decisions are repeatedly encountered and the application of heuristics becomes automatic (Rasmussen, 1986). Similarly, but requiring slightly more effort, the decision maker may re-enact exploration of the decision space by recalling previously formed evaluations for each alternative, and selecting the one with the highest overall evaluation: this is termed affect referral (Wright, 1975).

1.6.10 Combined Strategies

Decision makers are adaptive, both across and within decisions. Sometimes a particular decision will elicit a combination of different decision strategies, sometimes even a combination of compensatory and non-compensatory strategies. However, there are certain combinations that are common and are worth mentioning specifically. The most common combinations involve the use of EBA: EBA and WADD, and EBA and MCD. In other words, common combinations involve the narrowing of possible alternatives according to key attributes (EBA), and then the more careful examination of the select few alternatives (WADD for the most intense processing, MCD for less demanding processing).

1.6. 11 Measuring cognitive effort involved in decision heuristics

All of the decision strategies outlined above incur a different cognitive cost. While this is assumed in this thesis and not explored in itself, it is useful to illustrate how these cognitive costs have been measured and demonstrated in past research. A clear demonstration of the differential cognitive cost of the various strategies should further reinforce the position of the E-Af (Payne *et al.,* 1993) and by association the notion of a hierarchy of adaptivity. In addition, the concept of a decompositional approach to decision making is critical for this thesis. Although decision making will be examined in more general terms of the sequence of information acquisition rather than in the specific set of decision steps listed here, it is important to stress the decompositional nature of decision making.

Shugan (1980, p.100) suggested that effort or 'the cost of thinking' could be represented by 'a measurable unit of thought.' Huber (1980) and Johnson (1979) suggested that choice strategies could be decomposed into smaller units. Each strategy would consist of a certain number of these components, and the number of components would be indicative of how much cognitive effort each strategy required. These units of mental activities were termed, independently by both Huber and Johnson, as *elementary information processes* (EIPs). Examples of EIPs include mental operations, such as reading a piece of information into short term memory, comparing the values of two alternatives on a particular attribute, or multiplying a probability of outcome with a subjective weight for an attribute. Johnson and Payne (1985) and Bettman, Johnson, and Payne (1990) suggest a specific set of EIPs that have proven very useful in the context of researching the decision strategies outlined above. These are outlined in Table 1.1.

Table 1.1: Elementary EIPs used in decision strategies (from Payne, Bettman, & Johnson, 1993, p. 77)

EIP	*Description*
READ	Read an alternative's value of a particular attribute into short term memory (STM)
COMPARE	Compare two alternatives on the value of a particular attribute
DIFFERENCE	Calculate the difference between the values of the

	relevant attribute for both alternatives
ADD	Add the values of attributes within an alternative together
PRODUCT	Weight one value by another, or a value by a probability
ELIMINATE	Remove an alternative or an attribute from consideration
MOVE	Move on to the next element of the external environment
CHOOSE	Select preferred alternative and stop the process

Bettman *et al.* (1990, p. 114) argue that this particular set represents 'a theoretical judgement regarding the appropriate level of decomposition for decision strategies.' Note that each type of EIP may occur multiple times in any given strategy, in different orders, and that some may not be employed for certain strategies. The number of EIPs employed for a particular decision is a function of the specific strategy(ies) employed, the size of decision space as defined by the number of attributes and alternatives, and the specific values of the information provided (Bettman *et al.*, 1990). More comprehensive, consistent strategies such as WADD require more EIPs than the EBA strategy, for example. Decision spaces that are larger also tend to require more EIPs. Even when an economical strategy is being used there is still more information to search than in a small decision space. In addition, decisions where a greater number of attribute values surpass cut-off levels, or where the difference between attribute values is less, will require more EIPs. Bettman *et al.* (1990) specify that these rules are assumed in the context of a decision space that is read in a 'natural' reading order for the Western world, i.e. top to bottom, left to right, as their research was conducted in a Western context. In addition, because the READ and the MOVE EIPs are not independent, the MOVE operator is often incorporated into the READ function and not mentioned separately in most research. Payne *et al.* (1993) have provided a great deal of support for the EIP approach in conceptualising and measuring the effort involved in executing decision strategies such as those mentioned above. They found EIPs offered excellent models of cognitive effort, as predicted by response latencies and subjective reports of decision difficulty. They also found that EIPs were largely independent across strategies; this is critical if EIPs are to be considered a common 'language' of cognitive effort (Bettman *et al.*, 1990). Initially, each of the EIPs was assumed to be equal in terms of effort, however, this assumption was subsequently modified and it is now recognised that some EIPs are more effortful than others, but again this can vary in different circumstances.

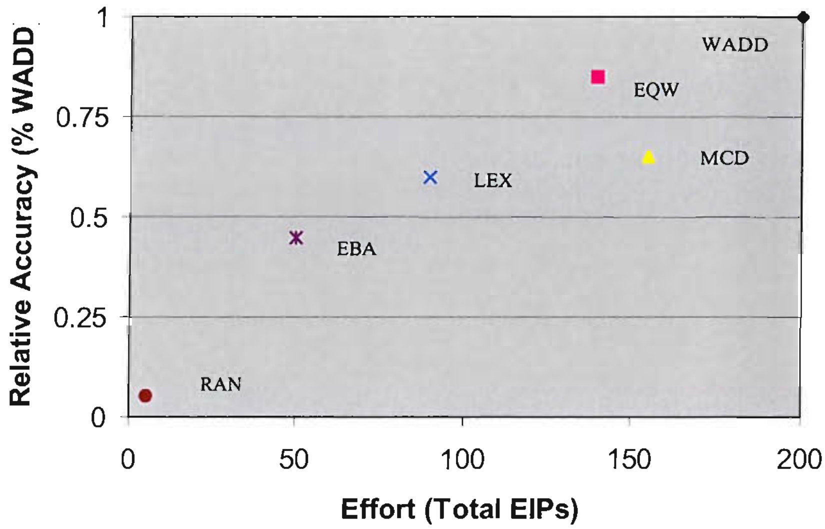

Figure 1.4 Effort and accuracy levels for various strategies (from Payne et al., 1993, p. 93)

Payne *et al.* (1993) provide an overview of where each of the major decision strategies lies in terms of cognitive effort, as measured by the absolute value of the count of EIPs needed to execute that particular strategy, when compared against the standard accuracy provided by normative models (in this case WADD) (see Figure 1.4). This allows the determination of which strategies are actually more cognitively demanding. Naturally, the specific amount of cognitive effort (i.e. number of EIPs) is not exactly consistent across decisions or decision makers, however the differences in cognitive effort between strategies will always be roughly equivalent. Thus, for example, for any one decision and decision maker, the WADD strategy will always have more EIPs than a LEX strategy.

Much evidence for EIPs underlying decision strategies was gathered through process tracing software initially developed by Payne and colleagues called Mouselab (Payne *et al.,* 1993). This will be described in much greater detail in Chapter 2.

1.6.12 Section summary

The decision strategies outlined in detail in this section are defined primarily by different combinations of the general decision strategy properties detailed in Section 1.5. Specifically, each decision strategy may be identified through determining if it is compensatory or non-compensatory, if it involves consistent or selective processing, how much information is processed, if it is alternative- or attribute-based, etc. (see Table 1.2). This is critical to recall at a later points in this thesis, when information acquisition patterns across decision spaces will be examined in light of these determining factors to judge broadly which type of strategies are being used.

A great deal of the focus in decision making has been on non-compensatory models, as compensatory models tend to demand more cognitive effort, which decision makers rarely have at their disposal. However, this focus on non-compensatory models has been criticised for several reasons. First, there is evidence that decision makers employ both compensatory and non-compensatory strategies for different tasks, or even within the same task (Beach, 1993; Payne, 1976; Payne *et al.*, 1998). Second, non-compensatory models have been criticised for the lack, or problematic nature, of statistical procedures to fit to these models (Elrod, Johnson, & White, 2004). Elrod *et al.* point out that the number of parameters estimated by the EBA (Tversky, 1972), for example, is not well-defined and, therefore, cannot be statistically modelled and tested. Third, the range of application of the traditional decision strategies across decision types is sometimes limited: for example, EBA was developed for binary attributes, and the EQW heuristic assumes attributes are expressed on a common scale. Fourth, and a much more general criticism relating to the nature of psychological behavioural data, it has been argued that the decision tasks constructed in research are designed to demonstrate best the superiority of non-compensatory models. As such, it remains unclear how the use of all decision strategies translate to the real world (Elrod *et al.*, 2004). From these criticisms, researchers have sought to develop more flexible models, that incorporate the possibility of employing both compensatory and non-compensatory strategies on the same task, in a way that is more clearly outlined and integrated than simply 'a combination of strategies.' In this thesis, the stand-alone decision strategies outlined above will be the focus of research, as it is felt that it is critical to develop accurate measures and data analysis paradigms of these before more integrated models are explored. However, it is important to recognise that more integrated, descriptive models exist.

Table 1.2: Properties of the main decision strategies (from Payne et al., 1993, p.32)

Heuristics	Comp (C) vs. non-Comp (N)	Info ignored? Yes (Y) vs No (N)	Consistent (C) vs. Selective (S)	Attribute (AT) vs. Alternative (AL) based	Evaluation formed? Yes (Y) vs. No (N)	Quantitative (QT) vs. Qualitative (QL) reasoning
WADD	C	N	C	AL	Y	QN
ADDIF	C	N	C	AT	Y	QN
EQW	C	Y	C	AL	Y	QN
EBA	N	Y	S	AT	N	QL
SAT	N	Y	S	AL	N	QL
LEX	N	Y	S	AT	N	QL
RAN	N	Y	S	AT	N	NA
MCD	C	Y	C	AT	Y	QN
FRQ	C	Y	C	AL	Y	QN

Note. WADD = Weighted additive rule; ADDIF = Additive difference model; EQW = Equal weights heuristic, EBA = Elimination by aspect; SAT = Satisficing; LEX = Lexicographic heuristic; RAN = Random choice; MCD = The majority of confirming dimensions heuristic, FRQ= Frequency of good and bad features heuristic

The next section of this chapter examines some of the factors that may influence decision making, and that may contribute to strategy selection both in terms of what strategies are available in the individual's 'adaptive toolbox,' as well as contributing to the cognitive demands of the task that determine which strategy will be employed. It would be impossible to outline all of the possible factors that could affect decision making, and it is not necessary to examine the ones which are not of primary interest to this thesis in huge detail. The factors of interest to this thesis (time pressure, decision complexity, and cognitive resources) will be discussed extensively in the relevant chapters. Rather, in this introductory chapter, only three factors will be examined for each branch of the tripartite model of decision making which will be outlined in Section 1.7, to illustrate some of the potential challenges and influencing factors decision makers face.

1.7 Challenges to actual decision making: Internal, external, and decision factors

From a psychological viewpoint, decision making is a particularly rich subject. It can be argued that it is the highest function on the psychological totem, building on everything from the most basic cognitive function of perception, through to the progressively more complicated and higher functions of attention, memory, learning, language, problem-solving, and reasoning. The structure of decision making is equally complex, building on a multitude of strategies and smaller units of information processing (EIPs).

Earlier in this chapter, the concept of the decision maker as adaptive was introduced: decision making is an adaptive process, which is contingent on a variety of factors from the specific decision and the decision environment, to the decision maker themselves. Einhorn and Hogarth (1981) highlight the volatility of the decision making process when they note that 'the most important empirical results in the period under review *(1950s-1981)* have shown the sensitivity of judgement and choice to seemingly minor changes in task' (p. 61). It must be highlighted immediately that the potential number of influences (based on these minor changes) that could affect decision making is almost endless: not only do individual factors alter the process, but multiple combinations of manifold factors may have unique influences on the decision making process. Research has tended to study potential influences in isolation, or at least in small combinations of two or three, to learn their basic effects on the decision making process, and to avoid making larger, predictive models of decision making.

In this section, the focus will turn to some selected examples of external, internal, and decision factors that have been shown to influence the process of decision making. The factors in this section have been selected as they have been well-researched, and are thought to provide a good illustration of this range of factors.

It can be argued that the conceptualisation of how external, internal and decision factors influence the cognitive demands of the task is unclear. Payne and his colleagues, as well as many other researchers, conceptualise these factors in a binary way: task effects and context effects. According to Payne *et al.* (1993, p. 22):

> 'Task effects describe the factors associated with the general structural characteristics of the decision problem, including response mode, number of alternatives and attributes, time pressure, information display mode, and agenda constraints. Context effects refer to those factors associated with the particular values of the objects in the decision set under consideration, including similarity and the overall attractiveness of alternatives. In general, the values of context factors are more dependent on individual perceptions than the values of task factors.'

In other words, Payne *et al.* (1993) believe one class of factors is related to task effects, which can include factors relating to the decision itself (e.g. response mode) and to the environment in which the decision is taking place (e.g. time pressure). Context effects relate more specifically to the decision set at hand (confusingly, as do some task effects) but Payne *et al.* (1993) claim that context effects are more subjectively determined than task effects. However, it is argued that this division between task effects and context effects as groupings of factors that can affect a decision is too simplistic. It is decision-focused, in the sense that all of the influences are linked to the decision itself, and as such is limited in scope. It does not provide sufficient separation between features in the decision space that will remain constant across time (the decision maker may revisit a decision at different points), and those that change; for example a decision maker may ponder a particular decision for a period of a week. At different points in time across the week, the decision may be constant (in that it may retain the same number of attributes and alternatives) but the decision maker may be vastly different (in terms of mood, fatigue, etc.) and the decision environment will change (they may be considering the problem at home, then at work). As shall be demonstrated, all of these factors have effects on cognitive and information processing, and this will have effects on decision making.

As such, a tripartite descriptive model of decision making based on three categories of factors that can affect decision making (external, internal, and decision factors) will provide the framework for this thesis, rather than a model based only on a division between task effects and context effects as proposed by Payne *et al.* (1993). While it is recognised that a tripartite model is not without criticisms, it is believed to be a stronger, more inclusive model than a binary distinction between the types of factors that influence decision making.

Specifically, the three branches of the tripartite model are: internal factors, which relate to the decision maker themselves; external factors, which relate to the environment in which the decision is being considered, and decision factors, which relate to the structure of the decision itself. These examples will be considered in the context of the E-Af (Payne *et al.*, 1993), which is the framework explored in this thesis. Within this context, these influences are thought to limit the amount of effort that can be expended and thus accuracy that can be obtained. The constraints placed on the decision maker by these three factors render the decision maker unable to use optimal strategies (such as the WADD), so that they must select alternative strategies based on their personal judgement of effort/accuracy goals. It is critical to note that this tripartite 'model' of decision making is a descriptive one, not a predictive one, designed simply to provide a conceptual and theoretical framework for decision making research. Clearly it is also reductionist and simplistic, in the sense that the combined effects of the vast number of strategies cannot be measured, but this is necessary, at least initially. Some of the simple factors discussed may be part of larger, super variables, which encompass a variety of lesser factors (for example, the overall competing attentional demands of the environment may be quantified from a range of sources, such as noise level, distractions from people in the vicinity, how biologically comfortable is the environment, and so on).

However, despite these criticisms, it is felt that a somewhat simplistic division into the three categories of external, internal and decision factors provides a useful, conceptual framework within which to operate.

All of the factors across the three branches of the tripartite model relate to the cognitive load of any particular decision. The overall level of cognitive demand of a decision can be defined simply in terms of two theoretical measures, which are drawn from the three branches of the tripartite model: the level of difficulty of the task and the level of complexity of the task. Both concepts represent an objective level of demand, and are related to the idea of cognitive effort: the more complex/difficult a decision, the more cognitive effort is required. Thus, as decision complexity and/or difficulty increase, given that cognitive resources are limited, the decision maker is more constrained in the strategies they can employ.

In this thesis, task complexity is defined by decision factors alone: factors that are specific, stable and inherent in the decision, which do not change over time. In other words, task complexity is represented by the size and nature of the decision space. Task difficulty, on the other hand, is determined by the external and internal branches of the tripartite model. As such, the level of task difficulty is determined by arguably more fluid factors, relating to the environment in which the decision is being made, and the cognitive state of the decision maker at that specific point in time. In other words, the difference between task difficulty and task complexity is that complexity is inherent to the task itself, whereas task difficulty refers to the broader context in which the decision is considered, and as such is more variable. Both task difficulty and task complexity translate to both subjective perceptions of demand by the decision maker, and objective demand in terms of information processing (for example, the number of EIPs involved in the decision). The general trend, as will be illustrated subsequently, is that an increase either in task difficulty or task complexity leads to greater usage of non-compensatory decision strategies.

The list of factors that determine the task's overall level of cognitive demand and subsequently influence the decision making process in terms of strategy selection are many, and it would be impossible to provide, not least explain in detail, an exhaustive list. Through the course of this thesis, one factor judged to be of great importance in decision making from each branch of the model will be studied: the decision factor of interest is the number of attributes and alternatives in the decision (related to task complexity), the external factor of interest is time pressure (related to task difficulty), and

Table 1.3: A tripartite model of factors of interest in this thesis

Influencing factor	**Cognitive demand**	**Operationalised by**
Decision factors	Task complexity (specific, stable, inherent)	Number of attributes and alternatives
External (Environmental) factors	Task difficulty	Time pressure
Internal (Participant) factors	Task difficulty	Cognitive resources ↓ by ageing ↑ by expertise

the internal factor of the amount and integrity of cognitive resources as defined by ageing and expertise (which relates to task difficulty) demands. These factors will be discussed comprehensively at relevant points throughout the course of this thesis, but will not be discussed in this section. Instead, this section will focus on three alternative examples from each of the three branches of the tripartite model to illustrate the general concept of challenges to decision making.

1.7.1 External Factors

External factors refer to factors in the environment in which a specific decision is made at any given point. They may relate to environmental context (time pressure, distractions), social factors (social accountability of the decision, group versus lone decision making, issues of competition), or the use of decision aids (paper-based or technological). Within the E-Af, each of these factors is thought to relate to the concept of decision difficulty: if the decision is made more difficult as a result of any one of the following factors (or lack thereof, in the case of decision aids), this will lead to an increased likelihood of the use of more economical, non-compensatory, cognitive strategies. To illustrate the impact of external factors on decision making, several of the factors mentioned above will be explained in more detail in this section. Time pressure will be examined further in Chapters 3, 5, 7, and 9.

1.7.1.1 Distractions to the decision maker – The impact on attention

Attention is considered to be the mechanism for continued cognitive processing (Pashler, 1998). While there is a debate that some processing may precede conscious attention, attention is considered to support the bulk of cognitive processing (Broadbent, 1958; Deutsch & Deutsch, 1963; Treisman, 1960). Specifically, attention is the gateway to working memory, and also supports working memory. As such, the sum total of the cognitive resources available to an individual comprises of attention and working memory capacity (Kahneman, 1973). Critically, attention and working memory are limited; there are only so many stimuli that can be processed (Kahneman, 1973; Sperling, 1960; Wickens, 1984). As such, attention is also selective; the individual may allocate attention to the stimuli/tasks that they judge appropriate. This system is not perfect, as sometimes distractions capture attentional resources without sanction from the individual (Cherry, 1953; Moray, 1959; Wood & Cowan, 1995). If there are competing demands on attention, it will be divided across the relevant tasks. Naturally, this implies that less attention will be available for each task, and performance will be more susceptible to interference and distraction (Hirst, Spelke, Reaves, Caharack, & Neisser, 1980; Spelke, Hirst, & Neisser, 1976; Wickens, 1984). In terms of decision making, if the task demands exceed capacity, decision making is likely to be affected.

Kahneman (1973) has elaborated a capacity model of attention, which suggests that the inability of humans to perform two tasks at once may not derive from a bottleneck of demanding stimuli at any stage of processing (as suggested by Broadbent, 1958; Deutsch & Deutsch, 1963; Treisman, 1960), but rather from a generalised depletion of a limited pool of resources. This resource theory is based on the general principles of attention: the assumption that attention is a resource that can be allocated to a task, and the assumption that it is limited. Kahneman proposes that information will be processed until all available processing resources are being employed. If two competing tasks, together, demand less than or equal to the amount of resources available, they will both be successfully completed. However, if a competing task demands more attention than the main task, either they will both be completed in a compromised manner, or one will be selected at the expense of the other.

The implication of distractions in the decision environment is clear. If competing demands and distractions are present, the decision maker's attention will be compromised, and s/he will not be able to attend to the decision space adequately, or at all. As such, it is likely that the decision will be compromised. Even resource-saving decision strategies may not be sufficiently economical to operate with the amount of resources available. Research into social policy and political decisions has demonstrated that even simple, unfavourable signal to noise ratios are enough to distract the decision maker, resulting in inferior decision making (Tetlock, 1992). As well as competing task demands, physical aspects, such as pain, also demand attention from the decision maker (Mirksy, Anthony, Duncan, Ahearn, & Kellam, 1991).

1.7.1.2 Social accountability

Social accountability relates to the degree to which the individual's decision will be scrutinised by any number of individuals, and thus creates a need for the decision maker to construct compelling justifications for their decisions. This is a particularly pertinent issue for social policy makers, government, and business organisations, where public accountability, media scrutiny, and hierarchical leadership structures demand accountability (Tetlock, 1992).

The effects of social accountability on cognition are varied, but essentially increased accountability places greater cognitive demands on the decision maker, as it creates pressure for more careful consideration of the decision space, more multi-dimensional, and self-critical thinking (Tetlock, 1992). In addition, accountability necessitates both the consideration of more information and more comprehensive integration of this information. In other words, accountability increases the likelihood of the use of more complex information processing strategies (such as compensatory decision strategies) and increases the cognitive demands of the decision task, increasing decision difficulty (Tetlock, 1985).

Accountability has both positive and negative implications for decision making. In an optimal cognitive environment, one where task demands can be met by cognitive resources, accountability is a positive factor for decision making in that it encourages more thorough consideration of the decision. Specifically, research has indicated that decision makers who are more accountable use more complex decision strategies in selecting alternatives from a decision space (McAllister, Mitchell, & Beach 1979), show increased self-awareness of the determinants of their judgements (Cvetkovich, 1978; Hagafors & Brehmer, 1983), process persuasive messages in more detail (i.e. systematically) rather than superficially (or peripherally: elaboration likelihood model, Petty & Cacioppo, 1986; Chaiken, 1980), and are more discriminating and responsive to evidence provided (Tetlock, 1985). According to the E-Af, this increased investment of cognitive effort is likely to result in a 'better' decision. In addition, research has demonstrated that increasing social accountability can lessen the effect of cognitive biases such as primacy effects (Tetlock, 1983), fundamental attribution errors (Tetlock, 1985), over-confidence effects (Tetlock & Kim, 1987), and sunk-cost effects (Simonson & Nye, 1992).

However, as cognitive resources are limited and can be made more so by varying cognitive demands on the decision maker, it is unlikely that optimal cognitive environments are common in the real world. In order to maximise accuracy while conserving cognitive effort, decision makers adopt strategies and heuristics in the face of social accountability. Social accountability also renders the decision maker more vulnerable to be swayed by the introduction of 'poor alternatives' to the decision space (Simonson, 1989). Specifically, these 'poor alternatives' are either irrelevant, or dominated alternatives, which means they have lower values on all attributes compared to the other alternative(s) in the decision space. There is also an increased tendency to stick with the status quo, when the decision involves changing something of a substantial nature, such as social policy (Tetlock & Boettger, 1994). In addition, Tetlock and Boettger (1994) demonstrate that there may be potentially serious consequences to social accountability, as it leads to increased postponement and passing the decision on to superiors in situations that require rapid responses for life or death outcomes.

One of the most common means to conserve cognitive effort in the face of social accountability is to adopt an acceptability heuristic, where the decision maker simply anticipates what the most preferable decision would be for the individual/parties to whom they are accountable, and selects that alternative (Tetlock, 1992). This eliminates the need for the decision maker to construct counter-arguments or additional justification for their decision, and, as a result, is less cognitively-demanding.

Thus, when presented with increased social accountability, decision makers are as susceptible to cognitive shortcuts and biases as they are when faced with increased decision difficulty of any origin. Again, although the strategies adopted by decision makers in the face of social accountability appear to violate normative decision making, in terms of an adaptive or 'functionalist' approach, these strategies are nonetheless fundamental for providing descriptive models of decision making.

1.7.1.3 Group influences: Conformity

One of the many group influences that can affect behaviour is conformity, or the tendency for individuals to alter their perceptions, opinions, and behaviour to ways that are consistent with group norms. This may not merely refer to a superficial change as seen in the acceptability heuristic. Indeed, conformity can result in the individual believing that their perceptions, opinions, or behaviours are independent of the influence of the group, regardless of what they felt prior to exposure to the group: this is called private conformity (Buehler & Griffin, 1994). As social animals, humans find it very difficult, even distressing, knowingly to breach social norms (Milgram & Sabini, 1978). Classic studies by Sherif (1936) and Asch (1951) illustrate the power of conformity.

Sherif (1936) demonstrated that judgements, which varied greatly when participants were asked privately and individually, converged when participants were questioned in a group setting. Interestingly, each group developed their own set of social norms for the judgement. Sherif's study was powerful, however, it is likely that participants were unsure of their own judgements, and simply used others' as a guideline, or benchmark.

Asch (1951) demonstrated an even more powerful instance of conformity: even when individuals were sure of their own judgements, they conformed to group norms even when it was obvious that they were erroneous.

It is clear that conformity is a powerful phenomenon. Social psychology researchers have presented different reasons why people might conform. First, they may conform through informational influence; the importance placed here is on being correct, and people believe that if more people agree on something, it is more likely to be 'right' and 'true' (Deutsch & Gerard, 1955). Second, individuals may conform through normative influence, which relates directly to the group dynamics, in that people agree with the norm because they fear the consequences of appearing deviant (Deutsch & Gerard, 1955). Research indicates that the perceived consequences of deviance exist, as individuals who stray from group norms tend to be disliked, laughed at, ridiculed, and even rejected (Levine, 1989; Schachter, 1951).

Certain factors render conformity more or less likely to occur in any given situation. First, group size is important: conformity increases with group size, but only to a point (Asch, 1956; Gerard, Wilhelmy, & Connolly, 1968). Beyond a group size of three or four individuals, additional individuals do not increase the level of conformity experienced within the group (Mullen, 1983). Second, individuals need to be aware of the norms for conformity to occur. Cialdini, Reno, and Kallgren (1990) conducted a series of studies which illustrated that norms are only likely to influence individuals when they are 'activated,' i.e. when the individual is made aware of them. Third, the presence of an ally (someone whose opinion/decision/attitude concurs with the individual in question) can dramatically reduce the incidence of conformity. This is because an ally reduces the stress of being a single deviant, validates the decision/attitude/opinion of the individual, and can shatter the illusion of a unanimous group decision which reduces the normative pressure to conform (Allen & Levine, 1971). Fourth, conformity is susceptible to individual differences: simply, some people are more likely to conform than others. While consistent personality traits predicting conformity have been hard to determine (Asch, 1951; Moscovici, 1985), age and gender differences have proved more reliable (Gavin & Furman, 1989; Sistrunk & McDavid, 1971), with women and adolescents being the most likely gender and age groups to conform. This illustration of conformity highlights the fact that decision makers also do not operate in a social vacuum, when they are making decisions in a group, this may substantially alter both the decision making process and the decision outcome.

1.7.2 Internal Factors

Internal factors relate directly to the individual, and their status at any given time at which a specific decision is being made. Internal factors include the individual's mood, factors that affect their top-down processing such as their expectations of the situation and the knowledge of decision topic, their personality (how confident they are, if they are risk-seeking or risk-averse in nature), gender, fatigue, motivation, intellectual ability, and individual working memory capacities. Internal factors have a broad influence on decision making, largely determining how much effort is available to devote to a specific decision. This, coupled with past decision making experience, determines which decision strategies will be used. It has already been mentioned that even the range of decision strategies available to the individual is a result of their own personal life experience and, as such, the adaptive toolbox is, in itself, an internal decision factor. To illustrate the impact of internal factors on decision making, several of the factors mentioned above will be explained in more detail in this section. Cognitive resources, operationally defined by ageing and expertise, will be examined in detail in Chapters 5, 6, 8, and 9.

1.7.2.1 Emotional State

No single agreed definition of emotion exists within Psychology, however, Kleinginna and Kleinginna (1981) conducted a meta-analysis and suggested that 'emotion is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can:

(a) give rise to affective experiences such as feelings of arousal, pleasure/displeasure;

(b) generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labelling processes;

(c) activate widespread physiological adjustments to the arousing conditions; and

(d) lead to behaviour that is often, but not always, expressive, goal directed, and adaptive.'

(Kleinginna & Kleinginna (1981), p. 355).

The intensity of the emotion and, subsequently, the level of arousal of the individual, can influence cognition. A mild level of emotional arousal can lead to increased attention to the current situation, whilst too much arousal leads to cognitive disruption and disorganisation (Hebb, 1972), through both increased vigilance and increased threat avoidance (Mogg, McNamara, Powys, Rawlinson, Seiffer, & Bradley, 2000). The implications for this in terms of decision making are as follows: increased attention is synonymous with applying cognitive resources, and therefore decision accuracy is more likely to be higher if attention is higher. Thus, mild levels of emotional arousal may be seen to optimise decision making, while too much arousal may be detrimental.

However, different individuals have different thresholds for arousal and disorganisation, and some even manage to function effectively in the face of very strong arousal (Brehm, Kassin, & Fein, 1999). This high level of tolerance may be innate, or may be gained through experience. This has important implications for professionals who operate in the face of great stressors, such as firemen, emergency personnel, flight traffic controllers, and police officers (e.g. Flin, Salas, Strub, & Martin, 1997; Tyhurst, 1951).

The emotional state of an individual, or their mood, has other effects on attention. 'Mood congruence' refers to the fact that when an individual experiences a mood, they are more likely to attend to stimuli that correspond to the emotion, rather than to those that do not.

As a result of this mood-driven allocation of attention, the individual is more likely to learn about events that are congruent with their mood at the time of acquisition (Bower, 1981).

Emotional state clearly influences attention, which in turn relates to judgements and decision making. Research demonstrates that one's mood influences both the judgements made about other individuals, as well as inanimate objects (Isen, Shalker, Clark, & Karp, 1978). Mood can also influence individuals' judgements about the frequency of risks in the environment. Johnson and Tversky (1983) demonstrated that being in a bad mood leads individuals to overestimate the potential risks of the environment, such as the frequency of different illnesses and types of fatalities, while being in a good mood leads individuals to underestimate these risks. In addition, moods can influence how the individual judges the situation in terms of their attributions. In a study by Keltner, Ellsworth, and Edwards (1993), participants who were in an angry mood tended to attribute the possible cause of a hypothetical event, such as missing a flight, to other people; whereas participants who were in a sad mood tended to ascribe the situation to external events, simply 'bad luck.' Mood can also influence memory. Research has found that more information is recalled when the individual is in the same mood they were in at the time the memory was formed (Bower, 1981; Godden & Baddeley, 1975). This is likely to apply to previously learned decision strategies as well, and thus may affect decision making.

The emotional state of an individual not only influences wider judgements made about the world, others, and situations; it can even influence basic functions. Emotion can influence the most basic level of cognition: perception. It has been demonstrated that judgements of similarity or difference between visual patterns can be influenced by emotional state (Dror, Péron, Hind, & Charlton, 2005). In addition, it has been proposed that mood even affects which information decision makers will rely on: in general, individuals in happy moods are more likely to rely on general knowledge structures using a top-down strategy, whereas individuals in sad moods are more likely to rely on the specifics of the present situation using a more bottom-up strategy (Igou & Bless, 2005).

1.7.2.2 Expectations

From the most basic level of cognition upwards, it can be argued the context of a situation can create expectations which influence how individuals perceive, manage, and respond to it. In other words, the world is often processed in a more top-down (cognition-driven) manner, rather than a bottom-up (data-driven) fashion. On the most basic level of perception, a simple demonstration indicates how the context (i.e. letters or numbers) affects what is being perceived (the item in the centre of the image) (see Figure 1.5).

Figure 1.5: An example of top-down processing

Despite being constant, when the individual reads from left to right, the image in the centre appears to be a letter; whilst when reading from top to bottom, it appears to be the number thirteen.

That even 'objective' visual stimuli can be interpreted differently depending on the context in which the stimuli are considered is due to the fact that no external stimuli can be considered to be perceived objectively. The human cognitive system receives stimuli through multiple sensory routes and interprets these stimuli in accordance with the individual's knowledge, expectations, hopes, fears, mood etc. As Dror writes, "The mind and the brain are dynamic systems that play active roles in how we perceive and construct realities" (Dror, 2005, p. 763).

Human cognition is not simply influenced by expectations on a perceptual level. The individual's expectations can influence how people judge situations, perceive reality, and make decisions. In general, humans are susceptible to various confirmation biases, which relate to the tendency to seek, interpret, and create information in ways that are consistent with existing beliefs. Again, in one sense, this is cognitively economical: it spares additional cognitive expenditure on the 'objective' and exhaustive examination of information. However, it also leads to errors in interpretation and judgements.

Confirmation biases manifest themselves in several ways. First, humans tend to exhibit belief perseverance, where prior beliefs are maintained even when they have been discredited (Anderson, Lepper, & Ross, 1980; Darley & Gross, 1982). Second, humans tend actively to seek information that confirms an existing belief or hypothesis, rather than one that disconfirms it (Synder & Swann, 1978; Zuckerman, Knee, Hodgins, & Miyake, 1995). In this sense, the very information on which decisions are made is biased and incomplete. Third, information presented to the individual which discredits their existing beliefs is often ignored and, similarly, individuals tend to ignore alternative explanations or options that may fit with the available data as well the existing belief does (for reviews, see Evans, 1982; Gilovich, 1991).

It is clear that individuals seek information that concurs with their existing beliefs. Context is an influential tool which creates expectations, or beliefs, and thus can predispose humans to see what they wish to see, to focus on information that supports their decisions rather than disproves them. A study by Dror, Charlton, and Péron (2005) demonstrated that presenting identical information in different background contexts was sufficiently strong for participants (in this case fingerprint experts) to make a decision that conflicted with their original one.

Another account for a phenomenon that can drive, but primarily reinforces, cognition and judgements is cognitive dissonance theory (Festinger, 1957). Cognitive dissonance refers to the very strong motivation for humans to maintain cognitive consistency, a state of mind where one's beliefs, attitudes, and behaviours are all compatible with each other (Abelson, Aronson, McGuire, Newcomb, Rosenberg & Tannenbaum, 1968). Discrepancies, or disagreements, between any particular beliefs, attitudes, and behaviours, lead to a state of tension, which is cognitive dissonance. This is very unpleasant, and humans are strongly motivated to eliminate this tension. This can be achieved either by changing the attitude in question, changing the perception of the behaviour, by adding additional, consistent cognitions (even ones that go against common sense), minimizing the importance of the conflict, or reducing accountability by reducing perceived choice. In terms of decision making, cognitive dissonance is clearly a substantial influence, particularly in justifying a decision once it has been made. Generally, when an individual has made a decision, they seek to rationalise what they have decided (and thus eliminate cognitive dissonance) by exaggerating the positive features whilst minimizing the negative features of the chosen alternative, and concurrently minimizing the positive and maximizing the negative features of unselected alternatives (Brehm, 1956; Knox & Inskter, 1968).

1.7.2.3 Personality

Personality theory is a well-studied area in psychology, although personality theorists differ quite dramatically in their approach to the topic. Some theorists believe that personality refers to permanent traits in the individual that are common to all; this approach is termed the nomothetic approach (Eysenck, 1954). Other theorists focus more on the uniqueness of each individual, and do not strive to outline common 'types' or 'traits': this is termed the idiographic approach. As such, a common definition of personality is hard to find. A contemporary definition is that "personality is a dynamic organisation, inside the person, of psychophysical systems that create a person's characteristic patterns of behaviour, thoughts, and feelings" (Carver & Scheier, 2000, p.5). Most personality research within the field of decision making has examined decision outcomes, rather than the effect of personality on the information acquisition process underlying decision making. Within this methodology, personality factors such as how risk seeking (Williams & Noyes, 2007), or how optimistic or pessimistic (Ludwig & Zimper, 2006,) a decision maker is affects decision making

In the context of this thesis, it is important to recognise that individuals personalities' will influence how they interact with their environment, which information in the environment they attend to, the range of experiences which leads to the expectations and attitudes that influence information processing, and even what decisions they are faced with. It has been demonstrated that individuals high in openness-to-experience (from Eysenck's Big 5 nomothetic personality traits) were significantly more influenced by anchoring cues (in the context of framing) relative to participants low in this trait (McElroy & Dowd, 2007).

More generally, one well-know nomothetic theory of psychology, which assumes all individuals can be placed on a continuum of personality dimensions as operationalised by scales, is Eysenck's type theory (1947). One of his most famous scales is the extroversion-introversion (E) continuum. In terms of the E continuum, a high scorer (an extrovert) is:

> 'sociable, likes parties, has many friends, needs to have people to talk to and does not like reading or studying by himself. He craves excitement, takes chances, often sticks his neck out, acts on the spur of the moment, and is generally an impulsive individual.' (Eysenck, 1965).

Extroverts actively seek out a range of new and exciting stimuli and, as such, arguably extend the range of their experiences. As outlined above, they also tend to take more risks, which will influence the decision alternatives they select. On the other hand, a low scorer on the E continuum (an introvert), is:

> 'a quiet, retiring sort of person, introspective, fond of books rather than people, reserved and distant except to intimate friends. He tends to plan ahead, 'look before he leaps' and distrusts the impulse of the moment...(he) places great importance on ethical standards.'(Eysenck, 1965).

Introverts do not seek the same level of stimulation and new experience as extroverts, and are much more cautious. This also has implications for decision making, possibly rendering introverts more liable to higher effort expenditure in terms of attention than extroverts; thus they may be more likely to employ compensatory heuristics compared to extroverts. This is only one example from a range of personality research, of how individual differences in personality are likely to impact decision making strategy selection and use.

1.7.3 Decision Factors

Decision factors refer to the actual features of the decision in question. Within the E-Af, each of these factors relates to the concept of decision complexity: increased complexity on the basis of any one of the following factors will lead to an increased likelihood of the use of more economical (non-compensatory) cognitive strategies. In this section, some key decision factors that influence decision making, and specifically a shift in decision strategies due to increased decision complexity, will be explored in detail as examples. These include response mode, similarity of alternatives, and information display. Other well-examined decision factors include agenda effects (the effect of placing a constraint on the decision maker in terms of the order in which elements in the choice set are considered, Tversky & Sattath, 1979); attribute range effects (the effects of increasing the variance on attribute values across alternatives, as the alternatives become more dissimilar, Beattie & Baron, 1981; Goldstein, 1990; Meyer & Eagle, 1982); and comparable and non-comparable alternatives in a choice set (comparing across categories, for example having some money to spend and choosing between a new kitchen, a holiday, and a new car, Johnson, 1988). Other factors that may be influential include the perceived risk of the outcome to the individual, the personal value of the outcome (Petty & Cacioppo, 1986) or decision importance (McAllister, Mitchell, & Beach, 1979), the degree of certainty of the outcome, and the overall quality of the data in the choice set (Payne *et al.*, 1993).

This section will aim to provide an indication of how decision factors in general may affect the underlying decision process (as well as the outcome). One of the most obvious decision factors to be manipulated is the size of the decision space, i.e. the number of alternatives and attributes that constitute the decision. However, decision complexity as defined by increasing the number of attributes and alternatives will be explored in detail in a Chapters 2, 4, 6, and 8, as the decision factor of interest to this thesis, and as such will not be further discussed here.

1.7.3.1 Response Mode

The idea that the way a decision is framed influences decision making has been discussed in Section 1.2.3. However, the way a decision maker is asked to select their preferred alternative can also influence the decision making process. In decision making research, there are several different ways in which decision makers can respond to a decision, which fall into two categories of response mode: the first based on a choice task and the second on a judgement task. The choice task, which is the most common in real life, involves presenting the decision maker with a number of alternatives and asking them to select their preferred choice (i.e. which gamble do you prefer?). Judgement tasks, on the other hand, generally involve sequentially presenting individual alternatives, and asking the decision maker to judge them in terms of their subjective attractiveness (Payne *et al.*, 1993). Specific judgement responses include a bidding mode (what is the minimum amount for which you would sell this gamble?), and a rating mode (how attractive is this gamble on a scale of 1 to 10?). A variation on the standard judgement task response is a matching mode, where the decision maker is asked to complete the missing value for one alternative in a pair so that the two alternatives are equal in subjective value.

The phenomenon of preference reversal discussed in Section 1.2.2 is a classic example of how response mode can alter decision making (Slovic & Lichtenstein, 1968). Slovic and Lichtenstein discovered that when decision makers were presented with a certain decision with alternatives A and B, decision makers overwhelmingly selected A when the response mode was the choice mode, but overwhelmingly selected B for the same decision when the response mode was changed to a bidding mode. Preference reversal violates the concept of procedure invariance (closely related to axiom transitivity), which states that preferences should remain constant for a particular decision when measured in strategically equivalent ways. This notion is rooted in the idea that decision makers have a 'master list' of preferences that is rigid, and is simply consulted in any situation to reveal consistent preferences. However, the entire notion of contingent decision making demonstrates that this concept has little validity. Tversky, Sattath, and Slovic (1988) note that the evidence suggests that preferences are constructed during the decision making process. This implies that observed preferences are constructed both from the decision maker's core values and the decision strategies underlying that particular decision; this makes the selection and use of decision strategies critical to decision outcomes.

Response modes can also lead to the compatibility effect (Slovic, Griffen, & Tversky, 1990). When provided with two types of information in making a decision (for example a company's market value and its profit rank for the current financial year), decision makers tend to focus on the type of information that is relevant to the response mode. If the decision is to judge the company's market value in the following year, decision makers will focus on the market value information; however when asked about profit ranking, they will focus on the profit rank information. Strategy shifts in line with the compatibility effect have also been demonstrated (Tversky *et al.*, 1988; Fischer & Hawkins, 1993). Tversky *et al.* first posited that certain types of response modes will elicit qualitative responses, while others will result in quantitative responses. Fischer and Hawkins take this further and make the compatibility effect more specific by suggesting that decision tasks that require qualitative responses result in the use of qualitative decision strategies, whilst tasks that require quantitative responses invoke the use of quantitative strategies. They also clarify the types of tasks that elicit different strategies: choice tasks and ranking tasks tend to invoke qualitative strategies, while response tasks based on rating, matching, and determining minimum selling prices result in quantitative decision strategies.

Any of the decision factors from the three categories of decision influences may be correlated with others, and response mode is no exception. Response mode effects, which remain one of the most widely studied of all the decision factors, may also be mediated by the internal factor of knowledge, or the familiarity the decision maker has with the decision in hand (Tversky *et al.*, 1988).

1.7.3.2 Similarity of Alternatives

Another widely studied decision factor is the similarity of alternatives on a particular decision task, and how this affects the decision process. Similarity is generally defined in terms of the size of differences between alternatives on the attributes in the decision; the smaller the difference, the greater the similarity. Context effects (as seen in Section 1.2.4) illustrate how the similarity of other alternatives, as illustrated by proximity in the decision space, can affect decision outcome. Manipulating 'inferior' alternatives so that they are more similar to other alternatives (in other words, they will be close in attribute values, but still less in terms of expected value) can cause different alternatives to be selected. This is in violation of Luce's choice model, or constant ratio model (CRM: Luce, 1959), which is a more specific principle of the choice principle of independence from irrelevant alternatives. The CRM states that:

> 'the probability of choosing an alternative X from some set of alternatives A is given by the following equation:
>
> $$P(X, A) = \frac{U(X)}{\Sigma U(A_i)}$$
>
> Where $U(X)$ reflects the utility of alternative X and $U(A_i)$ reflects the utility of each of the alternatives A_i contained in set A. Note that ratio $P(X,A)/P(Y,A)$ would be a constant if X and Y are two alternatives in A. This means that the relative choice probabilities of the two alternatives, X and Y, would depend on the utilities of X and Y but not on the values of the other alternatives in the offered set A. (Payne *et al.*, 1993, p. 54).'

In other words, the relative choice probabilities of choices X and Y in a particular choice set should be independent of the utility values of any other alternatives in the set. In addition to the illustration of context effects which violate CRM (outlined in Section 1.2.4), many other researchers have demonstrated that the values of the other alternatives in the choice set A affect the ratio of $P(X,A)/P(Y,A)$ (Debreu, 1960; Restle, 1961; Rumelhart & Greeno, 1971, Tversky, 1972). Results consistently indicate that the addition of an alternative to a choice set affects alternatives that are more similar to the added alternative than ones that are dissimilar to it. One of the main decision strategies, elimination by aspects (EBA), was developed to account for this effect of alternative similarity on choice (Tversky, 1972).

Notwithstanding the importance of alternative similarity effects on choice outcome, this thesis is more interested in the possible effects of similarity of alternatives on changes to the information processing strategies underlying decisions. In terms of cognitive effort, a high level of similarity between alternatives could have two possible, and opposite, outcomes. First, the cognitive demands of the task may be less if decision alternatives are more similar, as there may be fewer dimensions to consider, and it may be easier to identify desirable alternatives as they group together in clusters on the relevant dimension. In a sense, these clusters of relevant alternatives may narrow down the search of the decision space, thus conserving cognitive effort. This view is supported by Shugan (1980), who believes that perceptual similarity of alternatives is inversely related to the cost of thinking associated with the various decision strategies. Shugan suggests that when alternatives are similar, fewer distinct dimensions will be considered, and thus the cost of thinking will be less. Somewhat contrarily, however, he also believes compensatory strategies will be more likely to be employed, which is odd given that, as was previously discussed, compensatory strategies are generally considered to be more cognitively demanding. Shugan proposed that the cognitive demands for a decision with high levels of similarity between alternatives is lower, despite the use of a compensatory strategy, precisely because the clusters of similar options leads to 'easy' compensations, or trade-offs. It is worth noting that Shugan defines alternative similarity slightly differently to the norm; his definition relates to the covariance structure across attributes, rather than the pure size of attribute differences.

The other option, which is possibly more intuitive, is that a greater similarity between decision alternatives demands a greater amount of cognitive effort (Butterworth, Zorzi, Girelli, & Jonckheere, 2001), in order to discern the differences between them and select the best one. Support for this view has been provided by various researchers, who have inferred that greater cognitive effort is visible through the use of compensatory decision strategies. Evidence for an increased use of compensatory strategies for a highly similar decision set includes the finding that an increasing amount of information from the decision set is acquired as the similarity between alternatives increases, and that the variability in search across alternatives decreases as similarity between the alternatives increases (Biggs, Bedard, Gaber, & Linsmeier, 1985; Bockenholt, Albert, Aschenbrenner, & Schmalhofer, 1991). Stone and Schkade (1991b) illustrate that the total time taken to make a decision is greater for decision sets with higher levels of similarity across alternatives. All of these factors, as will be discussed in Chapter 2, are indicators of the use of compensatory decision strategies.

It is worth briefly mentioning a related decision factor to alternative similarity: the concept of correlated attributes across alternatives. In general, if alternatives are similar, the attributes will be positively correlated; while if alternatives are dissimilar, the attributes will tend to be negatively correlated. A great amount of research has been conducted on negatively correlated attribute structures, which tend to reduce the differences between alternatives in terms of overall value (the difference in value between the first 'best' alternative and the second 'best' alternative is smaller). As argued above, a reduction in the overall differences between alternatives' values may lead to a shift in decision strategies, probably to more cognitively effortful strategies. In general, research supports this claim, indicating that negatively correlated attribute structures tend to result in a greater amount of processing, less selectivity of processing, and more alternative-based processing (Bettman, Johnson, Luce, & Payne, 1993).

1.7.3.3 Information Display

The way the information is presented to the decision maker is critical to how the decision is processed, and its outcome. A range of specific factors relating to this concept has been studied, and some key factors will be mentioned here.

One decision factor relating to information display that has received a good deal of attention is the influence of the format in which attribute values are presented, on both decision outcomes and the underlying decision process. Most commonly, attributes may be presented numerically or linguistically, and the bulk of research in this topic has focused on the difference between the numerical and verbal representation of information. In terms of the underlying decision process, it appears that numerical information leads to more direct within-attribute comparisons, and interestingly less use of comparisons against a set criterion, or threshold (Huber, 1980). Verbal representations of attribute values tend to lead to more alternative-based processing, and the reduced use of cognitive operations related to compensatory decision strategies (Stone & Schkade, 1991b). More specifically, even within a representation type (numerical or verbal), the form in which the information is displayed is influential (Cipolotti, Warrington, & Butterworth, 1995). It has been demonstrated that when probabilities are displayed in simple form (.57) rather than complex form (563/985), they result in a lower rate of preferences reversals (Johnson *et al.*, 1988). It was suggested that the simple form demanded less cognitive effort to execute normative decision strategies, such as calculating expected value. While some of the issues relating to information display remain unclear (for example, the effects of different representations of information in a choice set), it is clear that information display is an important decision factor. However, more research must be conducted on this factor, including how comparing and integrating different representations of attribute information (both numerical and verbal, or even auditory and pictorial representations) within the same decision set affects the decision process.

Another key aspect of information display is the amount and quality of information provided. Slovic (1972) suggested a 'concreteness' principle, which refers to the fact that decision makers tend to use only the information that is explicitly and clearly displayed in the decision problem, and will only use it in the form in which is it presented. It has been suggested that this tactic is in line with the driving principle of cognitive economy. The implications are that the way the decision space is constructed in terms of information display will affect the underlying decision process, as well as the outcome. In a display designed to encourage alternative-based processing (organisation of products by brand), more alternative-based processing was observed (Bettman & Kakkar, 1977).

The emphasis on cognitive economy in terms of information display also highlights the difference between available vs. processable information. A great deal of information may be displayed to the individual, but it may not be processed if demands are too great. In a classic study of applied decision making, Russo (1977) demonstrated that shoppers were more likely to consider unit price information when the information was presented in the form of organised lists where the product prices were ranked in order of increasing price units, rather than distributed throughout a store. This information (unit price of each item) was always available to the shoppers, but individually on the basis of each item on separate shelves in the supermarket. Presenting the information in a comparison format, arguably an integration that immediately placed each unit price in a frame of reference, resulted in that information being used.

The quality of the information displayed to the decision maker is also important. Partially described, or information-poor, options will have an affect on the decision process. The decision maker may deal with incomplete information in several ways: first, they may simply infer missing values. Decision makers tend to draw on their knowledge of the other attributes for that alternative (or brand, for example), rather than information about the same (complete) attribute from the other alternatives.

Decision makers may deal with incomplete information simply by eliminating the alternative which contains the missing value, as a form of uncertainty avoidance (Jagacinski, 1991). Alternatively, they may continue to consider the attribute which contains missing values for one or more alternatives, but weight them less strongly than they would normally, or than they weight other common, complete, attributes (Slovic & MacPhillamy, 1974).

1.7.4 Section summary

The external, internal, and decision factors outlined here provide an introduction to the wide range of factors that may influence decision making. Later in this thesis, the external factor of time pressure, the internal factor of cognitive resources, and the decision factor of decision complexity will be examined in more detail. However, even a closer look at the aforementioned factors will not provide a complete picture of their influence. The biggest challenge to the study of decision making is that a distinctive decision situation is created at any moment, by the unique combination of the entire range of internal, external, and decision factors present at that time. Describing, and worse yet, predicting decisions and decision outcomes proves virtually impossible, as it is not a viable option to measure and account for each influencing factor. In order to arrive at a point where predictive decision models may be constructed, descriptive models must be improved. Recent decision models have adopted the descriptive methodology of structural equation modelling (SEQ), where the contributing influence of various factors to the decision outcome is quantified. SEQ is a very powerful statistical technique that, if sufficiently large samples are collected, can deal extremely well with large numbers of latent and extant variables, and can manage collinearity (Marcoulides, 1996). However, SEQ models are not predictive as such, as they are based on the retroactive assignation of standardised path coefficients. Thus, although SEQ is an interesting step forward, it is unclear if these models can handle a sufficient number of variables from the tripartite model to provide a comprehensive account of decision making. In addition, SEQ does not provide predictive models of decision making.

However, even if the field of decision making can never provide accurate, general, predictive models that can be applied to every decision, this does not render the field unworthy. A moderate understanding is better than none at all, and with time (in terms of quantity of research as well as improved technology to assist the research), deeper understanding will be attained. Decision making is too critical a cognitive function to be left unexplored.

1.8 Chapter summary

This chapter introduced a range of decision making research; first to provide a general level of understanding of the area, and second, to outline the key issues of interest in this thesis.

First, it examined classic normative decision theories such as Expected Value and Expected Utility Theory, and proceeded to demonstrate the challenges to normative theories, such as the Allais paradox, preference reversal, framing, and context effects, which highlighted the inadequacy of these theories to account for explanations of real-life decision making. This led to the development of descriptive decision theories such as Prospect and Regret theory, as well as the more recent descriptive theories, which are rooted in the cognitive framework and which stress that decision making is a dynamic, flexible process.

The chapter then moved into the more specific areas of interest to this thesis, starting by describing the fundamental assumption that underlies current research on human cognition (as well as this thesis), the idea of a human information processing system of limited cognitive resources. It then focused on how the trade-off between cognitive effort and decision accuracy renders the nature of decision making contingent on the interplay between task demands and the resources that can be brought to that task at any point in time. This was outlined in a description of Payne *et al.*'s Effort-Accuracy framework (Payne *et al.*, 1993). This point was taken further to illustrate humans as adaptive decision makers, who have at their disposal a range of different tools in the form of decision making strategies, which they can apply differentially to any given decision as a 'best fit' for the demands of that situation. This is the concept of 'the adaptive toolbox' (Gigerenzer *et al.*, 1999).

The chapter continued by focusing specifically on decision strategies as common heuristics in decision making under certainty, which may constitute an individual's adaptive toolbox.

General properties of decision strategies as a whole were outlined, before each of the common decision strategies was described and identified on the basis of these general properties; i.e. where each strategy can be categorised in terms of each property. Each of the decision strategies outlined describes a method of information acquisition which underlies the decision process. A method for quantifying the cognitive effort demanded by each strategy, in terms of elementary information processes (EIPs), was also discussed in order to illustrate the differential cognitive costs of decision strategies, which is a critical assumption in this thesis. Finally, the chapter outlined a tripartite model of factors that affect decision making: internal factors, external factors, and decision factors. The remainder of the chapter focused in detail on examples for each of these factors.

Sections 1.6 and 1.7, which outlined decision strategies and the tripartite model of factors that can influence decision making, are critical for this thesis, as the focus of the research described herein is an examination of the effect of one example of each of the three factors (operationalised as time pressure for the external factor, decision complexity as defined by the size of the decision space for the decision factor, and cognitive resources for the internal factor) on the information acquisition process (as defined by the decision strategies employed by the decision maker).

While this chapter has outlined some of the theoretical difficulties underlying decision research, the next chapter will begin to examine the influence of a decision factor, decision complexity, on the information acquisition process underlying decision making.

Chapter 2.

Study 1: The influence of decision complexity on the information acquisition process underlying decision making in young adults

2.0 Introduction

In the previous chapter, it was proposed that the total task demand of any decision equates to the sum of decision complexity and decision difficulty. It was proposed that *how* decisions are made, i.e. the information acquisition process, is dependent upon the balance between task demands and the cognitive resources available for that task. This chapter reports a study which examines how increasing task demands by increasing decision complexity influences the information acquisition process underlying decision making.

Broadly, decision complexity is a judgement of the computational demand of a decision. It relates to changes in decision factors alone: in other words, to characteristics about the decision itself, independent of the decision maker and the decision environment. Arguably the most basic decision factor linked to decision complexity is the size of the choice set, or decision space (Hogarth, 1975; Payne, 1976, 1982). This is determined simply by the number of alternatives and the number of attributes for a particular decision; and it is by this that decision complexity will be operationalised in this study.

According to the general Effort-Accuracy framework (E-Af; Payne, Bettman, & Johnson, 1993), increasing the complexity of a decision is synonymous with increasing the task demand of the situation. This increase in task demand necessitates an increase in the amount of cognitive effort necessary to maintain accuracy levels. Once the cognitive resources available to the decision maker have been exceeded, the decision maker will be forced to adopt cognitively economical decision strategies, in an attempt to maximize decision outcome (accuracy) while minimizing cognitive effort (Payne *et al.*, 1993: Swait & Adamowicz, 2001).

Thus, the E-Af predicts that, at the point where the decision maker's processing capacity (or cognitive resources) begins to be exceeded, steps must be taken to optimize the balance between task demands and processing capacity. The way in which the balance between task demands and task resources can be mediated is through the adoption of different decision strategies, namely switching from cognitively-intensive, compensatory strategies to more cognitively-economical, non-compensatory strategies (Payne *et al.*, 1993).

Previous research has supported this argument. Work that has previously been conducted on increasing the size of the decision space has tended to examine either the effect of increasing the number of alternatives *or* the effect of increasing the number of attributes, but not both. Studies have shown that increasing the number of alternatives causes shifts in decision strategies (Biggs, Bedard, Gaber, & Linsmeier, 1985; Billings & Marcus, 1983; Klayman, 1985; Onken, Hastie, & Revelle, 1985; Payne, 1982; Payne, Bettman, & Johnson, 1988; Payne & Braunstein, 1978; Shields, 1980). In general, as alternatives increase from two to many, decision makers employ non-compensatory decisions strategies such as elimination by aspects (EBA: Tversky, 1972) and lexicographic (LEX), rather than weighted additive (WADD: see Chapter 1, Section 1.6). Payne (1976) found that while most decision makers shifted to non-compensatory strategies as the number of alternatives increased, individuals varied in whether their non-compensatory search patterns became more attribute or alternative-driven. There is some research to indicate that increasing decision complexity results in more mixed patterns of search: more attribute-based at the beginning of the process, and more alternative-based towards the end, similar to a combination heuristic such as EBA + WADD (Bettman & Park, 1980). However, this effect is not as consistent as the shift from compensatory to non-compensatory strategies (Payne & Braunstein, 1978).

Increasing the number of attributes in the decision space also leads to increased cognitive economy. It appears that the way the decision space is examined becomes more selective as the number of attributes increases. That is, individuals ignore less relevant or important information and focus on attributes that they view as priorities (Grether, Schwartz, & Wilde, 1985; Grether & Wilde, 1983). As discussed in Chapter 1, this attribute-led method of searching the decision space is a key element of most cognitively-economical strategies such as EBA, LEX, and the majority of confirming dimensions (MCD). In addition, cognitive economy is also visible through increased use of non-compensatory decision strategies as the number of attributes increases (Biggs *et al.*, 1985; Sundstrom, 1987); although Payne (1976) and Olshavsky (1979) found that increases in the number of attributes do not, in themselves, translate to changes in decision strategy selection.

Thus, there is considerable research to demonstrate that increasing the decision space via increasing the number of attributes or alternatives leads to increased cognitive economy. However, none of these studies above examined the pure effect of increasing decision space size on information acquisition. The studies listed above were either conducted under conditions of uncertainty (i.e. the outcome the decision maker selects is not guaranteed), or only increased attributes or alternatives, but not both. Both of these designs make interpretation of the results difficult: the first adds extra computational demands in the form of probability information, in that each attribute value must be considered in terms of the probability outcome. This additional computational demand may affect the information acquisition process independently of any increase in decision space size. The second results in a disproportionate decision space that can, in itself, influence search patterns (Payne *et al.*, 1993).

Thus, this study is a partial replication of Payne (1976). The aim of this study was to examine if and how the information acquisition process is affected by increasing decision complexity in terms of cognitive effort, in a 'cleaner,' more idealised decision space which eliminates the confounding variables detailed above. An idealised decision space contains no additional computational demands on the decision maker in terms of the information in the decision (no weighting, no probability calculations), and increases the decision space proportionately in terms of attributes and alternatives. Thus, computational complexity is defined in terms of the size of the decision space: low computational demand is operationalised by a simple 4x4 decision matrix (4 attributes, 4 alternatives), and high computational demand by an 8x8 matrix. The information acquisition process was defined and measured in terms of three key factors: the amount of information processed in the decision, the selectivity of the search, and the pattern of the search (i.e. attribute- or alternative-led). This study examined how increasing task demands by increasing complexity influences the amount of information processed in the decision, as well as the selectivity and pattern of the search.

The amount of information processed is defined by four factors: the total time taken to make the decision, the number of information acquisitions made, the time spent on each acquisition, and the proportion of time spent on the subjectively most important attribute. If decision complexity does not lead to cognitive economy, or cognitive streamlining, computational expenditure may be expected to be equivalent across conditions. In terms of the total time taken to make the decision, it is expected that the total time taken to make the 8x8 decision would be four times that of the 4x4 condition, given the relative difference in the sizes of the decision spaces. However, if the computational demand of the 8x8 condition does lead to cognitive streamlining, this may be seen in a total decision time for the 8x8 condition that is proportionately less than (i.e. less than four times as great), or equal to, the time taken to make the 4x4 decision. Similarly, if the number of information acquisitions made in the 8x8 decision is less than or equal to four times as many as the 4x4 condition, this may be indicative of cognitive streamlining, even though the absolute number of acquisitions may be higher than that of the 4x4 condition. In terms of the average amount of time spent per acquisition, an equivalent amount across conditions would indicate equivalent levels of computational demand per item. Cognitive streamlining would be evident through a decline in the average amount of time spent on each acquisition in the 8x8 condition relative to the 4x4 condition. The final measure relating to the amount of processing is the proportion of time spent in the most subjectively important attribute. If the decision maker devotes the same computational effort to each attribute, an equal proportion of time will be spent in each one. However, if computational effort is being conserved, this should be reflected in an increase in the proportion of time spent on the most important attribute.

Selectivity relates to how consistently items are considered in the search process. In terms of selectivity, a strongly cognitively-economical search would result in increased selectivity, i.e. more variability, in terms of what information from the decision space is processed. It is likely that as computational demand increases, the variance across attributes and alternatives will increase, as some items are considered less, or not at all. However, increased selectivity may not be immediately indicative of increased cognitive economy, particularly if the time spent on each acquisition decreases. Decision makers may not need to be selective in the first stages of cognitive economy if they are able first to conserve effort by speeding up their acquisitions.

In terms of the pattern of search, the bulk of previous research indicates that searches become increasingly attribute-led in the face of decision complexity, as decision makers prioritise the decision dimensions of value to them (Grether & Wilde, 1983; Grether *et al.*, 1985; Payne *et al.*, 1988). In other words, decision makers tend to search across attributes, rather than across alternatives, when trying to conserve computational effort. However, some research indicates that people may also become more alternative-led (Payne, 1976), and that increasing decision complexity merely renders a search pattern, be it attribute or alternative-led, more extreme. This study will explore the effects of complexity on the three dependent measures above: amount of information processed, selectivity of processing, and pattern of search.

None of these dependent measures should be considered in isolation, particularly those that are related to the amount of information processed. For example, if the decision maker cognitively-streamlines to the point where they consider only very few attributes, they may spent a greater amount of time considering this information. Examining only the average time spent per acquisition would indicate an absence of cognitive economy; however, when it is considered against the number of acquisitions, it is clear that cognitive economy is occurring.

2.1 Method

2.1.1 Participants: This study used a within-participants design. 36 (26 females, 10 males, age *M* 21, *SD* 2.81 years, range 18-35) University of Southampton undergraduates participated for course credits. As the concept of cognitive capacity is critical to this study, all participants were administered a standardized test of working memory (Digits Backward, a subtest of the WAIS- III, Wechsler, 1997). This sample of young adults had an average working memory span of 7 digits (*SD* 1.3, range 4-10). As a span of 4 is arguably outside of the normal range (Miller, 1956), the degree of correlation between span scores and the dependent variables were examined. Span score did not co-vary with any of the dependent variables.

2.1.2 Mouselab methodology: Decision strategies are determined by the process of decision making, specifically, the process of information acquisition. This process is usually measured through a process tracing paradigm, whereby details about the information acquisition are recorded in terms of the order of item acquisition, the duration of time spent acquiring items, and total time to decision. In this study, a process tracing software package called Mouselab (Johnson, Payne, Schkade, & Bettman, 1986) was used. This system presents the decision on the screen of a personal computer in the form of a matrix of decision information. The alternatives are listed down the left hand side of the matrix, while the attribute information is listed across the top (see Figure 2.1). Only one cell (any one attribute value for a particular alternative, for example alternative A, attribute 4) can be seen at any one time: the boxes remain closed until they are selected by the decision maker. The decision maker uses a mouse to move the cursor to select which cell they wish to see. The cursor must remain touching some part of the cell for it to remain open; once the cursor moves completely off the cell, it closes again. Each cell may be viewed any number of times, and for any length of time. The participant may make a choice, i.e. select which alternative they desire, at any point, by selecting the radio button to the left of the desired option at the bottom of the screen.

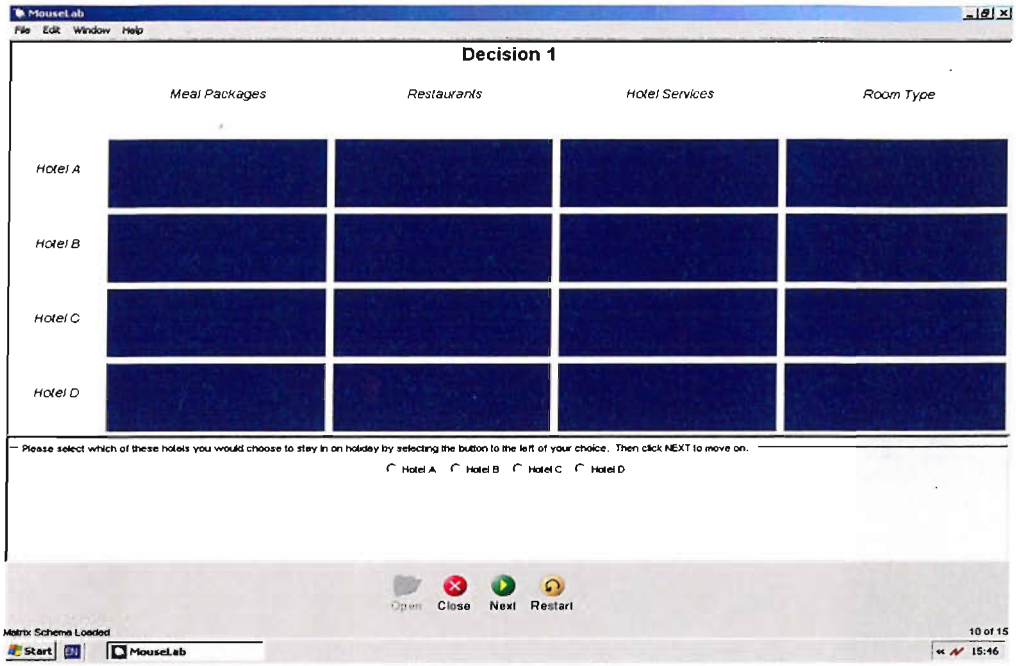

Figure 2.1 Illustration of a decision in Mouselab on the computer screen

The Mouselab program records the order in which cells are viewed, the amount of time each cell is open, the final decision, and the total amount of time taken to make that decision. Response times are recorded to 1/60th of a second (Payne *et al.*, 1988). Further measures can be inferred from the basic Mouselab data output: these will be discussed in detail in the dependent measures section below.

2.1.3 Stimuli: The stimuli in this study were 4 sets of decisions (4 low complexity, 4 high complexity), relating to selecting an hotel for a holiday. Hotel attributes for the decision were selected after examining holiday brochures, as they were judged to contain key factors in hotel desirability.

Baseline condition, low complexity matrices contained 4 alternatives, each with 4 attributes (4x4) giving a total of 16 pieces of information. The high complexity condition matrices contained 8 alternatives with 8 attributes (8x8), giving a total of 64 pieces of information.

The size of the decision matrices, and thus decision complexity levels, was selected on the basis of several critical factors. It was important to keep the number of alternatives and attributes equivalent, as disproportionate matrices can themselves influence search patterns (Payne *et al.,* 1993). It was important that the independent variable in this study was represented by two distinct levels of decision complexity. In terms of the low decision complexity condition, it was felt that 2x2 and 3x3 matrices provided too few items of information for participants to consider the decision worthy of effort, and a 6x6 matrix (consisting of 36 items of information) was judged to be already complex as defined by computational demands. This is supported in a study by Wichary, Orzechowski, Kossowska, Markovic, Slifierz, and Bukowski (2005), where working memory was exceeded by decision complexity in a 4x6 matrix (24 items). A 4x4 matrix, with 16 pieces of information, was judged to be sufficiently demanding to require effort on the part of the participant, but not so demanding that non-compensatory strategies would be largely employed. This assumption is supported by a classic study by Payne (1976), who found that even in the most simple condition (2x4), only .845 of the decision space was searched, even though compensatory strategies were predominantly being employed. In his 4x4 condition, three-fourths of the decision space (.792) was searched, and compensatory strategies largely employed. In terms of the high complexity condition, it was felt that an 8x8 matrix would be cognitively-demanding for most decision makers. Again this assumption is supported by Payne (1976), whose 8x8 condition resulted in approximately half (.479) of the decision space being searched, which indicated the increased use of non-compensatory strategies on this task. It was felt that if the decision space were too complex, the decision maker would be completely overloaded and simply guess by strategies such as random choice (RAN: Hogarth, 1975). Some researchers have claimed that a minimum of 10, 18 or even 27 alternatives (interestingly they do not specify a number of attributes) is necessary for cognitive strain (Jacoby, Speller, & Kohn, 1974; Lurie, 2002; Malhotra, 1982b). However, in this study, decision information was not presented simultaneously (as will be discussed in the next section); participants could only see one piece of information at any one time, thus ensuring working memory was truly being taxed in terms of the retention and recall of information. Thus, decisions constituted of 16 items of information and no time pressure are defined as low task demand in the context of this thesis, while decisions that are constituted of 64 items of information and no time pressure are defined as high task demand.

Each piece of decision information in each cell in the matrix was represented in numerical terms on a scale ranging from 1-4, with 1 being the best, or highest, level of that attribute, and 4 being the worst, or lowest, level of that attribute. Numerical representation was selected over verbal representation in order to keep the processing demands of each piece of information equivalent. It was important that in each decision space no single alternative was objectively the best, i.e. had a higher value as defined by the sum total of its attribute values. It was important that the individual searched a neutral decision space, to find the alternative that was best for them. Thus, in order to avoid the complications of dominated alternatives and 'best options,' all of the alternatives were assigned an equal value in terms of overall attribute weight. For the 4x4 matrices, the values 1, 2, 3, 4 occurred once for each alternative, while for the 8x8 matrices they occurred twice. All eight attributes relating to hotels (room type, meal packages, restaurants, hotel services, facilities, complimentary extras, transfer time to the nearest airport, distance to the nearest town) were used in the 8x8 condition, but only ones judged to be the most influential in a pilot study (room type, meal packages, restaurants, hotel services) were used in the 4x4 condition. This was to ensure that all 4x4 decisions were equivalent. In addition, this is arguably ecologically valid, as numeric weightings are used in hotel brochures too, via star systems (1, 2, 3 star, etc.), and on online sites such as Trip Advisor.

The order of the attributes in each matrix was counterbalanced using a Latin Square design (for the 8x8 condition, this was done separately for the first four attributes and the second four attributes), resulting in 4 unique 4x4 and 4 unique 8x8 matrices across participants (see Appendix A for an example). In addition, the order of presentation of the 4x4 and 8x8 matrices was counterbalanced across participants. All decision matrices were presented, and data recorded, within Mouselab on an IBM Pentium 4 PC with a Windows XP environment (screen resolution 1024 x 768 pixels, diameter 15.5 in).

2.1.4 Procedure: The data collection for the high complexity and high demand conditions for all participants, across all quasi-experimenal groups, occurred in one session. The three conditions presented to each participant (baseline 4x4, 4x4 time pressure, 8x8) were counterbalanced across participants: the 6 resulting orders of conditions were divided equally across all participants. Participants were seated approximately 45 cm from the computer screen, and were told to follow the instructions on the screen. There were two practice trials, which were presented in 6x6 matrices and consisted of selecting a flat to rent. Participants were then asked to complete the experimental decision tasks. They were given an unlimited amount of time in which to complete the decisions. Participants were also given a crib sheet that they could refer to throughout the session, with a key to attribute values (1-4, 1 = excellent, 4= poor) and descriptions of the attributes themselves (see Appendix C). After the decision had been made, participants were asked to rank all 8 attributes in terms of subjective importance on a scale of 1-8. Participants were also administered a standardised test of working memory span (Digits Backwards, WAIS III, Wechsler, 1997), and an estimate of intelligence (National Adult Reading Test, Revised; NART-R, Nelson & Willison, 1991).

2.1.5 Dependent measures: Seven previously published measures that relate to the total amount of information processed during the decision task, the sequence of information acquisition, and the selectivity of processing of the information available in the decision space, were used.

<u>Measures of total amount of processing:</u> The total amount of information processed during a decision is an index of the amount of cognitive effort expended on a decision task. More cognitive effort indicates a more intensive, compensatory decision strategy. One traditional measure of the amount of information processed during a decision task is the total time taken to make a decision (**TdTIME**: Bettman, Johnson, Luce, & Payne, 1993). A second measure, which is also denoted in seconds and milliseconds, is the average time taken per acquisition, **TperACQ**, i.e. the average amount of time spent in each information cell in the Mouselab decision matrix, from the moment the decision maker selected the information cell to the moment they moved away (Bettman *et al.*,

1993; Luce, Bettman, & Payne, 1997; Payne *et al.*, 1988, 1993). A third measure of the amount of information processed is the actual number of acquisitions made, i.e. the total number of times information cells were opened for a particular decision, including repetitions of acquisitions from the same information cell, **ACQ** (Bettman *et al.*, 1993; Luce *et al.*, 1997; Payne *et al.*, 1988, 1993). A final measure of amount of processing, giving a general indication of cognitive effort as well as the specific strategy employed, is the proportion of time spent in the decision maker's subjectively most important attribute, **PTMI** (Payne *et al.*, 1988; 1993).

Measures of selectivity of processing: Cognitively-intensive, compensatory strategies imply a consistent (i.e. low variance in the search pattern) pattern of information acquisition, while cognitively–economical, non-compensatory strategies imply a more selective pattern of information acquisition, represented by high levels of variance in the search pattern. Two measures of selectivity have been consistently employed in past literature (Bettman *et al.*, 1993; Luce, *et al.*, 1997; Payne *et al.*, 1988; 1993) and were used in this study. These relate to the variance in the proportion of time spent on each alternative (**VAR-ALT**) and each attribute (**VAR-ATT**) in the decision set, including those not viewed at all. Low levels of variance, which imply a consistent search, range from 0 - .020. A VARATT or VARALT measure of .020 - .039 implies moderate selectivity, while 0.040 + can be considered to indicate high levels of selectivity (Payne *et al.*, 1988).

Measure of the sequence of information acquisition: The sequence of information acquisition, which is also termed the pattern of processing, is determined by whether information acquisition is attribute or alternative-led. One measure, **PATTERN,** has been used in the literature to quantify this factor (Bettman *et al.,* 1993; Luce *et al.*, 1997; Payne *et al.*, 1988, 1993). Given the acquisition of any piece of information in the matrix, Payne (1976) argues that two scenarios for the acquisition of the next item of information exist. The first involves moving to acquire information about a different attribute within the same alternative; this is a Type 1, or alternative-led, transition. The second involves moving to a piece of information about the same attribute, within a different alternative. This is a Type 2, or attribute-led, transition. PATTERN is the ratio of the alternative-led (Type 1) less attribute-led (Type 2) transitions divided by the sum of Type 1 and Type 2 transitions.

$$\text{PATTERN} = \frac{t_1 - t_2}{t_1 + t_2}$$

PATTERN ranges from -1 to +1. The more alternative-led the sequence, the more positive the number; the more attribute-led the sequence, the more negative the number.

Traditionally, a shift towards cognitive economy (as represented by non-compensatory processing) was considered to be evident through all of these factors, i.e. a reduction in processing, with an increase in selectivity and an increase in attribute-led searching. However, this thesis will suggest that more subtle shifts along a continuum of compensatory to non-compensatory processing may be evident. As such, it is suggested that any change in any of these 3 categories towards the directions outlined above (decreases in cognitive processing, increases in selectivity, and increases in attribute-led searching) must be considered as representative of cognitive economy. A low demand decision is operationalised by a high amount of information processed (each attribute is acquired at least once, an average of minimum half a second is spent on each acquisition, an equal proportion of time is spent on each attribute, there is no selectivity of search across attributes or alternatives (VARATT and VARALT < 0.020), and the search pattern is alternative-led (or neutral). A moderate/ high demand decision is operationalised by a lesser amount of information processed (less acquisitions than the number of attributes available, half a second or less spent on each one, a significant increase in time spent on the subjectively most important attribute, selectivity of search (0.020 + for VARATT and VARALT), and an attribute-led search pattern.

2.1.6 Analysis: The normality distributions of each of the dependent variables, within complexity levels, were checked with the Shapiro-Wilks test. If variables violated normality assumptions, they were transformed, as recommended by Tabachnick and

Fidell (1996). Correlation coefficients between variables were calculated in order to identify co-linearity. Any variables with an R^2 approaching .90 would have been excluded, as advised by Tabachnick & Fidell (1996). A repeated measures MANOVA was then conducted on the transformed variables (Tabachnick & Fidell, 1996). Model fit was assessed by exploring the distributions of the residuals. If the residuals for any variables deviated significantly from normality, non-parametric univariate, repeated measures comparisons (Wilcoxon's Rank Sum) were conducted to confirm MANOVA findings. The dependent variables were then examined in terms of proportionality, as they relate to decisions of different sizes and equivalence must be considered. Predicted values of TdTIME and ACQ for the 8x8 condition were computed by multiplying TdTIME and ACQ values for the 4x4 condition by 4, as the 8x8 condition is 4 times larger. A paired samples t-test was conducted on the actual 8x8 values and the predicted 8x8 values of these measures. In addition, one sample t-tests were performed with PTMI variables, against their predicted values to examine if processing was consistent across attributes (100% / number of attributes); and also with PATTERN values and the optimal consistent search value of 0 (a value which indicates the search is neither attribute nor alternative-led), to determined how significantly attribute-or alternative-led the values were.

2.2 Results

With the exception of PATTERN, data were log transformed due to positive skew. None of the variables were excluded on the grounds of co-linearity (see Table 2.2). Table 2.1 contains raw score descriptives, for ease of interpretation.

2.2.1 The 4x4 condition:

In the 4x4 decision condition, if all items of information were considered equally, there would be an average of 2.96s and 2.19 acquisitions per item. If this is factored out in terms of alternatives, this would average at 11.84s and 8.92 acquisitions per alternative. As there were 16 pieces of information available in the decision space, this implies a number of repetitions of acquisitions, either 2 per attribute or multiple acquisitions on some attributes, less (or even none) on others. Participants spent, on average, 30% of the decision time considering values related to their subjectively most important attribute (PTMI).

Table 2.1 Mean dependent measures by decision condition

	4x4	8x8
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	47.47 (36.02), 6.96 - 164.32	69.72 (47.27), 15.33 - 234.71
ACQ	35 (36.02), 6 - 132	67 (49.90), 15 - 220
TperACQ (ms)	524 (176.43), 180.60 – 957.50	477 (142.04), 156.90 – 896.70
PTMI	.31 (.13), .12 - .69	.18 (.09), 0 - .38
	Measures of selectivity	
VARALT	.017 (.016), .001 - .050	.017 (.014), .001 - .063
VARATT	.016 (.017), .001 - .081	.016 (.046), .001 - .281
	Measure of information acquisition	
PATTERN	.197 (.418), -.667 – 1.0	.298 (.388), -.571- 1.0

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

If time were distributed equally across attributes, participants should have spent 25% of the time in each one. The difference between predicted PTMI (25%) and actual PTMI (30%) is significant, $t(35) = 2.69$, $p = .010$. Thus, in terms of information processing, the demand appears to be mild in the 4x4 condition. Participants were able to make multiple acquisitions and to take a reasonable amount of time to consider attributes and alternatives.

In terms of the selectivity of search, the results imply a consistent search as VARATT and VARALT are both low (Payne *et al.*, 1988). The pattern of the search suggests the use of a more alternative-based search, as there was a significant difference between a perfectly consistent search (0) and the reported 4x4 PATTERN value, $t(35)= 2.84$, $p = .007$.

Table 2.2 Correlation matrix for dependent variables: 4x4 above the diagonal, 8x8 below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.59‡	.08	-.18	-.37 †	-.27	.21
ACQ	.89 ‡		.14	-.14	-.39 †	-.34 †	.06
TperACQ	-.08	-.09		-.03	.17	.22	.11
PTMI	-.16	-.11	.01		.41 †	.22	-.36 †
VARATT	.20	.47 ‡	.23	-.01		.56‡	-.06
VARALT	-.49 ‡	-.53 ‡	-.06	.10	-.03		-.03
PATTERN	.28	.32	.03	-.02	.00	-.10	

Note. † = p <.05 level (2 tailed); ‡ = p < .01 level (2 tailed)

In terms of the selectivity of search, the results imply a consistent search as VARATT and VARALT are both low (Payne *et al.*, 1988). The pattern of the search suggests the use of a more alternative-based search, as there was a significant difference between a perfectly consistent search (0) and the reported 4x4 PATTERN value, $t(35)= 2.84$, $p = .007$.

2.2.2 The 8x8 condition:

In the 8x8 decision condition, if every item were considered equally, this would average at 1.09s and 1.05 acquisitions per item (less than half of the same values for the 4x4 decision). This equates to 8.72s and 8.24 acquisitions per alternative. Participants spent on average 18% of the decision time considering values appertaining to their subjectively most important attribute (PTMI), which is significantly more than they would have spent if time were distributed equally across attributes (12.5% of the time in each one), $t(35) = -842.40$, $p < .001$. Thus, in terms of information processing, the demand appears to be moderate/high in the 8x8 condition.

In terms of the selectivity of the search, the results suggest the use of consistent search strategies for this decision. In terms of PATTERN, the search appears to be significantly more alternative- than attribute-led, compared to a consistent search value of 0, $t(35) = 4.61, p < .001$.

2.2.3 A comparison of the 4x4 and 8x8 conditions:

In terms of the correlations between variables (see Table 2.2), the pattern of correlation is consistent between conditions. TdTIME was consistently significantly correlated with ACQ, and ACQ was consistently highly correlated with VARALT and VARATT (although the correlation between ACQ and VARATT was positive, while all other correlations were negative). It is logical to assume that a positive correlation between ACQ, and TdTIME, should exist, as TdTIME is contingent upon ACQ and/or TperACQ. However, VARATT and VARALT are not contingent upon the number of acquisitions made. Rather, a significant negative correlation between ACQ and VARATT and/or VARALT, in either condition, implies that participants are more selective (higher VARATT and VARALT values) when they search fewer attributes. In the low complexity condition, VARATT and VARALT were also positively correlated, although this relationship is not apparent in the high complexity condition.

A repeated measures MANOVA of complexity (4x4, 8x8) for the transformed dependent variables (TdTIME, ACQ, TperACQ, PTMI, VARALT, VARATT) and the variable PATTERN revealed a main effect of complexity, $F(7, 28) = 13.60, p < .001$. This arose through significant effects of complexity in TdTime, $F(1, 35) = 12.67, p = .001$, in ACQ, $F(1, 35) = 42.28, p < .001$, and in PTMI, $F(1, 35) = 14.88, p < .001$. No significant effects for complexity were found for TperACQ, $F(1, 35) = 2.43, p = .128$, VARATT, $F(1, 35) = 2.54, p = .120$, VARALT, $F(1, 35) = .07$, $p = .791$, or PATTERN, $F(1, 35) = 1.94$, $p = .172$. There was significant deviation from normality for the residuals of three variables (PTMI8, VARALT8, and VARATT8). Non-parametric comparisons of complexity level were conducted. There were consistently significant effects of complexity on TdTime, $Z(N{=}36) = -2.96, p = .003$, ACQ, $Z(N{=}36) = -4.72, p < .000$, and PTMI, $Z(N{=}36) = -3.48, p < .001$. As in the MANOVA, the following variables showed no effects of complexity: TperACQ, $Z(N{=}36) = -1.47, p = .140$, VARATT, $Z(N{=}36) = -$

1.51, $p = .120$, VARALT, $Z(N=36) = -.10$, $p = .918$, , and PATTERN, $Z(N=36) = -1.86$, $p = .064$.

However, the significant effects reported above are based on absolute values. In absolute terms, analysis revealed that TdTIME for the 8x8 condition was significantly higher than TdTIME for the 4x4 condition. However, if the proportionality of processing demands is considered, it would be expected that the 8x8 decision would take four times as long to make than the 4x4 condition if they both demand equivalent amounts of processing, as 16 items is 1/4th of 64 items. TdTIME was 47.47s for the 4x4 condition; this would predict an average TdTIME of 190.80s for an 8x8 decision. In fact, TdTIME in the 8x8 condition was significantly less than this, at 69.72s, $t(35) = -5.22$, $p < .001$.

Similarly, in absolute terms, the average number of acquisitions made in the 8x8 decision was significantly higher than the number made in the 4x4 condition. However, again if equivalence across conditions were considered, the average number of acquisitions in the 8x8 condition would be projected by the number of acquisitions per item multiplied by 64, i.e. 2.23 x 64 = 142.7. This is more than double the actual ACQ for the 8x8 condition. This difference is significant, $t(35) = -6.84$, $p < .001$. Thus, the relative amount of information processed (in terms of the actual number of items processed) in the 8x8 condition may be considered significantly less than would be expected from that of the 4x4 condition.

Proportionality between decisions for the PTMI measure must also be considered. The PTMI for each of the conditions was roughly only 5% greater for each of the conditions, at 31% in the 4x4 condition and 18% in the 8x8 condition, than the proportion of time spent in attributes if divided equally across attributes (25% and 12.5% respectively). While the standard statistical analysis appears, at face value, to suggest that participants were more efficient in terms of focusing on primary information in the 4x4 condition, on closer inspection the PTMIs of both conditions were equivalent, each at only 5% more than the expected value.

2.3 Discussion:

This study set out to examine the effects of increasing decision complexity (as defined by a proportional increase in the number of attributes and alternatives) in an 'idealised' decision space, on the process of information acquisition underlying decision making by young, healthy adults. It was found that increasing task demand from low complexity to high complexity resulted in cognitive streamlining in the information acquisition process, specifically in terms of the amount of information processed. In absolute terms, participants spent more time making their decision and made more acquisitions in the high complexity (8x8) condition than they did in the low complexity (4x4) condition. However, the average total time spent making the complex decision was proportionately significantly less than in the low complexity condition. In addition, the average number of information acquisitions made in the complex decision was relatively less than half of that predicted by the low complexity condition if computational equivalence were maintained. This may, in part, reflect the relative importance of the primary 4 attributes (the ones used in both studies). Participants may have spent relatively less time on the additional 4 attributes due to the fact that they were less interested in them. However, in any given decision, it is clear that not all attributes will rank in the same subjective position for the decision maker: there will always be some attributes that are more subjectively important than others. While the focus on the primary attributes may be the underlying mechanism behind the results presented herein (namely, relatively less processing on the high complexity condition), this is not inconsistent predictions of the E-Af. The E-Af suggests that an optimal decision is based on the consideration of all attribute values, as all of them would inform a comprehensive assessment of an alternative. If participants spend relatively less time than would be expected on those attributes deemed to be less important to them, this is precisely the shift towards more economical, selective, and non-compensatory processing that the E-Af would predict.

Generally, these results indicate that in the high complexity condition, participants were able to invest slightly more cognitive resources in absolute terms than in the low complexity condition, as they may not have exceeded their resource threshold in the low complexity condition. However, these differences must be considered in light of the cognitive demand of the high complexity task. The high complexity condition should demand four times the computational effort than the low complexity decision. However, the fact that information processing on the high complexity condition was significantly less than would be predicted by the baseline condition suggests that cognitive resources were exceeded and cognitive streamlining occurred.

While it may be concluded that decision complexity led to increased cognitive economy in terms of the amount of information processed, this does not appear to translate into increased selectivity of search, or a more attribute-led search process in the high complexity decision, compared to the low complexity condition. This is inconsistent with previous research, which has consistently demonstrated increased selectivity and more attribute-led searches as a result of complexity (Biggs *et al.*, 1985; Billings & Marcus, 1983; Grether & Wilde, 1983; Grether *et al.*, 1985; Klayman, 1985; Onken *et al.*, 1985; Payne, 1982; Payne *et al.*, 1988; Payne & Braunstein, 1978; Shields, 1980; Sundstrom, 1987).

It may be that this study is not inconsistent with previous research, but simply that it represented a different level of cognitive demand. As mentioned earlier, the nature of this decision was not equivalent to those employed in past research, which may account for the difference in results. For example, past research which examined the effects of increasing the number of attributes or alternatives has tended to use decisions under conditions of uncertainty, where decision outcomes are linked to different probabilities, or decisions involving money necessitating a calculation of value (Biggs *et al.*, 1985; Payne, 1975; Payne *et al.*, 1988; Payne & Braunstein, 1978; Wright, 1975). It was suggested, in the introduction, that this additional computational demand, as well as the use of disproportionate decision spaces (Biggs *et al.*, 1985; Billings & Marcus, 1983; Grether & Wilde, 1983; Grether *et al.*, 1985; Klayman, 1985; Onken *et al.*, 1985; Payne, 1982; Payne *et al.*, 1988; Payne & Braunstein, 1978; Shields, 1980) may be responsible for previous findings relating to clear shifts towards non-compensatory strategies. Taken together, this suggests that an increase in the absolute number of items in the decision space may not be the most powerful determinant of task complexity. It is possible that other decision characteristics are more critical, or, as is more likely, it is their combined effect that is critical for determining complexity, and as such, cognitive load. The added step of calculating probability for each outcome enhances the complexity of the decision; in other words, the addition of attribute weight information such as probabilities or financial value renders the cognitive handling of attribute information more effortful. Thus, a 4x4 decision under conditions of uncertainty may be greatly more complex than a 4x4 decision under conditions of certainty, because of the manipulations necessary to calculate the decision information.

Thus, this study provides evidence for cognitive streamlining as a result of decision complexity. This is visible through a decrease in the amount of information processed in the high complexity condition as compared to the low complexity condition. In addition, this study also provides some insights into the nature of decision complexity and the possibility of a hierarchy of response to increasing task demands. First, it suggests that responses to decision complexity cannot primarily be defined purely in terms of size of decision space. A pure measure of decision complexity, the proportionate increase of the decision space with clean information, indicates that even a decision with 64 pieces of information does not lead to strong cognitive streamlining. However, it is clear that an 8x8 pure, or 'idealised' decision, does reach a moderate level of decision complexity, which is useful for studying decision makers' adaptive response to increasing task demand.

With regard to this adaptivity, the fact that decision makers in this study respond with a more moderate level of cognitive streamlining than that seen in previous studies, where decision complexity was greater due to confounding variables, suggests a sensitivity to the balance between task demand and cognitive resources. This provides support for the concept of an adaptive decision maker (as discussed in Chapter 1), who matches cognitive resources to task demands contingent on the specific decision situation. However, while the E-Af (Payne *et al.*, 1993) implies a hierarchy of adaptivity, it tends to refer to one that is based on broad shifts in strategies, i.e. to strategies that change in terms of amount of processing, selectivity, and pattern of search. Only one study has stressed that strategies may shift subtlety by changes in any combination of the amount of information processed, selectivity, and/or search patterns (Payne, Bettman, & Luce, 1996). The study reported herein demonstrates that a subtle change (simply a decrease in the amount of processing) occurred in the context of this decision, which had a particular balance between task demand and resources. The subtlety of this change implies the hierarchy of adaptivity is even more sensitive than has previously been widely-acknowledged. In which case, across a range of tasks with unique matches between task demand and resources, a hierarchy of adaptive responses should become evident that involves subtle changes, as well as possibly major shifts in strategies. This notion of a sensitive hierarchy of adaptivity will be explored further and elaborated upon throughout the course of this thesis.

If there is a discrepancy between these findings and those of past research, it can also be explained with methodological criticisms about the nature of the dependent variables. First, the traditional measures used may not adequately reflect the information acquisition process. An example of the possible insensitivity of the dependent measures in this study is the measure of information acquisition, PATTERN. For example, several participants in this study had PATTERN scores bordering 0, indicating a search strategy that is neither attribute- nor alternative-led. However, a closer look at the sequences of information acquisition of these participants reveals that they were often guided primarily by their primary attributes, and once the highest value of that attribute was pinpointed across alternatives, the other attribute values of that alternative were searched to double-check the alternative as a whole was acceptable. Interestingly, this is a strategy that is not explicit in the literature – it results in a search that is driven by subjectively primary attributes, which then involves a check of the values of all of the attributes in the alternative. It is similar to the lexicographic (LEX) and elimination by aspects (EBA) strategies in the sense that the attribute of highest subjective value is selected, but here the similarity ends as no secondary attributes are considered. If only one attribute were considered in EBA and if the decision space contained attribute weights, it would be similar to a combination EBA + WADD strategy (Bettman & Park, 1980), which does tend to emerge when the number of alternatives increases. It is also similar to satisficing

(SAT) in the sense that if that alternative surpasses subjective cut-offs on all attribute values, it is selected. Thus, it is possible that less well-documented decision strategies were being employed here, ones that do not emerge as strongly as non-compensatory, selective, and attribute-led strategies. It is also possible that the dependent measures examined in this study were not sensitive to the use of combined strategies, and that these combined strategies were, in effect, cancelling each other out.

In addition, as Payne (1976) demonstrated, cognitive economy may not only be apparent in attribute-led search patterns, but may result in a polarisation of search patterns within a group. Thus, some decision makers may engage in a more extreme alternative-led search, and others in a more extreme attribute-led search. Analysis across group PATTERN data will, again, cancel out the effects of individual change. Each group of decision makers is different, and in groups in which this polarisation does not occur, searches may appear more attribute-led. Previous research may have been largely represented by this type of group. However, this study was not concerned with the use of specific decision strategies by each individual decision maker. This approach is too focused and reductive at this stage of research. At this point, this study is more interested in the broad changes in the information acquisition process: that is, if there is a general trend to the increased use of more cognitively economical strategies, rather than specifically what those strategies are. However, it is recognised that group data may obscure individual trends.

Further potential criticisms of this study lie in the use of MANOVA, as some measures violated normality assumptions. A closer inspection of the data revealed this was due to several extreme values on the dependent measures involved. Removing these 'outliers' would have been a possibility; however, a fundamental assumption of decision making data is that there are no 'abnormal' results, each step of the information acquisition process is simply a representation of how that individual made that decision. Since no individual will make a decision in exactly the same way, there is no assumption of normal distributions of response. As such, the decision was made to include these 'outliers' in the data analysis, and to run a parametric test, as MANOVA is a robust technique (Mardia, 1971; Tabachnick & Fidell, 1996). The results of the MANOVA were and will in future studies be confirmed by non-parametric analysis, where standardised residuals are not normally distributed.

It is possible that measurement failures in previous research may have overemphasised the ability of these measures to distinguish between types of strategies. Much of the evidence for the switch to attribute-led searches in the face of increased cognitive demands has been provided through correlational evidence, and when examined experimentally, strategy use is not always strongly linked to acquisition pattern (Senter & Wedell, 1999). Indeed, Senter and Wedell (1999) argue that shifts in acquisition pattern may reflect shifts in the implementation of a particular strategy, not a total change of strategy. They also argue that the defined strategies in the literature may not be as rigid as they are made out to be; they comment that the WADD strategy does not necessarily have to proceed in an alternative-driven search pattern, but may be implemented via an attribute-led search (Senter & Wedell, 1999). Thus, compensatory and non-compensatory strategies, as defined by global measures of amount of information processed, selectivity, and search pattern, may be harder to distinguish than past research has acknowledged. It is possible that a broader range of measures may be of use in determining any changes in information processing strategies, and this is an area that should be explored in future research. This will be discussed later in this thesis.

In summary, this study demonstrates evidence for increased cognitive economy in the face of increasing task complexity in a clean decision environment. An interesting question, which will be addressed in the next study, is whether similar results will be found when the task demand has decision difficulty as the source of computational demand, rather than task complexity. In other words, will an increase in task difficulty, as defined by time pressure, induce cognitive streamlining to a lesser, equal, or stronger degree than an increase in decision complexity could in this study? As well as exploring the effects of task difficulty on decision adaptivity, the next study will begin to examine the importance of demand source on information acquisition.

Chapter 3.

Study 2: The influence of decision difficulty on the information acquisition process underlying decision making in young adults

3.0 Introduction

Increasing the cognitive load, and hence task demand, of a decision may take two forms: increasing the amount of information to be processed, or reducing the amount of time available in which to carry out that processing (Wright, 1974). In the previous chapter, in which the first of these forms was examined, it was discovered that increasing decision complexity affected the information acquisition process by leading to cognitive streamlining. This was evident through a relative decrease in the amount of information processed, both absolute and relative. It was suggested that this may be indicative of contingent decision making. More specifically, it was suggested that a hierarchy of adaptivity exists, which is operationalised by the implementation of different decision strategies whose selection is dependent on the precise relationship between task demands and computational availability.

This chapter focuses on the second form of increased cognitive load outlined above, and reports a study which examined if and how the information acquisition process is affected by amplifying cognitive load through increased decision difficulty in an 'idealised' decision space.

Time pressure is an external factor in the tripartite decision model (see Chapter 1, Section 1.7), and is generally experienced when the time available for the completion of a task is perceived as being shorter than that normally required for the activity (Svenson & Edland, 1987). Time pressure is a mediator of decision difficulty, which is a measure of the computational demand of any decision made by a certain decision maker, in a particular environment, at a specific moment. Thus, an increase in time pressure is synonymous with an increase in task demand. According to the Effort-Accuracy framework (E-Af; Payne, Bettman, & Johnson, 1993), increasing task demand results in strain on the decision maker's cognitive resources, which results in the use of cognitively-economical decision strategies. Thus, the E-Af would predict that a mild/moderate increase in task demand, or time pressure, will actually enhance overall performance by the adoption of cognitively-efficient strategies.

An increase in task demand caused by increasing time pressure is particularly interesting, as time pressure is strongly related to stress and, by association, mood (Maule, Hockey, & Bdzola, 2000; Edland & Svenson, 1993). Stress is a well-documented factor, which has been shown to have both positive and negative effects on performance in a variety of cognitive tasks (Chajut & Algom, 2003). Most famously, the Yerkes-Dodson principle outlines that, up to a certain point, stress and arousal enhance performance. After this 'threshold,' however, stress begins to have a detrimental effect (see Yerkes & Dodson, 1908). As discussed in Chapter 1, mood has a considerable effect on decision making. The effects of stress on mood are mediated by factors such as how well the decision maker feels they can cope, and how important is the decision (Maule *et al.,* 2000).

Thus, the predictions of the Yerkes-Dodson principle on performance in relation to stress are consistent with those of the E-Af in decision making: mild/moderate time pressure should enhance performance, specifically through a shift to more cognitively-economical processing, which maintains acceptable levels of decision accuracy. Research has provided evidence that this is the case, although there is some disagreement as to the nature of this cognitive streamlining (Ben Zur & Breznitz, 1981; Miller, 1960; Payne, Bettman & Luce, 1996; Payne, Bettman, & Johnson, 1988, Payne *et al.,* 1993).

Three main theories of the effects of mild/moderate time pressure on decision making have been outlined in previous literature. Each of the theories represents a transition to cognitive economy and a certain level of adaptivity: the first two theories relate to what are termed 'micro' changes in decision making, while the third relates to 'macro' changes (Maule *et al.*, 2000). First, mild/moderate time pressure may result in an *acceleration* of information processing (Ben Zur & Breznitz, 1981); decision makers will attempt to process the same amount of information at a faster rate. Payne *et al.* (1988) demonstrated that, as time constraints increased, the amount of time spent processing an item of information decreased substantially (see also Payne *et al.*, 1996; Maule *et al.*, 2000).

Second, mild/moderate time pressure may result in the decision maker focusing on a subset of the most important information in the decision space; this is referred to as *filtration* (Miller, 1960). Filtration is likened to the concept of perceptual narrowing as a response to stress: this is reflected in a reduction in the range of hypotheses and actions considered (Keinan, 1987). Filtration can be seen in a shift to an examination only of subjectively important information (Payne *et al.*, 1988; Wallsten & Barton, 1982). Edland (1994) demonstrates that people focus more on positive information under time pressure, as negative information is too cognitively effortful in that it is more likely to lead to trade-offs in attribute values; i.e., compensatory processing. Other researchers have discovered filtration in the form of focusing on negative information in an attempt to minimize negative consequences (Ben Zur & Breznitz, 1981; Canavan, 1969; Webster, 1964; Wright, 1974), although this is more likely if the decision maker is accountable to others (Maule *et al.,* 2000; Wright, 1974). Conversely, time pressure can also lead to more global processing of the information in the decision space. Acquiring a little knowledge about all of the alternatives may represent a better strategy than detailed information about only a few alternatives (Payne *et al.*, 1993).

Thirdly, decision makers may react to time pressure by changing decision strategies, such as those discussed in Chapter 1, Section 1.6. Zakay (1985) hypothesized that decision makers would switch to more non-compensatory strategies under time pressure, and found evidence for increased use of the lexicographic strategy (LEX). However, Zakay focused on selectivity and not other measures, making it hard to distinguish filtration from a shift to more selective, but comprehensive, strategies (Payne *et al.,* 1988). Payne *et al.* did find that in addition to being more selective, as Zakay demonstrated, processing was also more attribute-based. This indicates an overall shift of strategy. Payne *et al.* also reinforced the notion of a hierarchy of responses to time pressure, dependent on its intensity. They suggested that filtration and acceleration are predominant under mild/moderate time pressure, while more severe time pressure (before the performance point is surpassed) leads to a shift in decision strategies which is characterized by accelerated processing, selectivity, and a shift to more attribute-based processing. However, other studies have failed to find evidence for such a strong shift to attribute-based processing (Payne, Bettman, & Luce, 1996).

While it has been argued that the processes of acceleration, filtration, and shifting decisions strategies are distinct, the evidence supporting such clear distinctions is sometimes lacking (Maule *et al.*, 2000; Payne *et al.*, 1993; Payne *et al.*, 1996). Maule *et al.* (2000) argue that acceleration and filtration are distinct mechanisms in their own right: they demonstrated that filtration is negatively correlated with acceleration. In other words, people tend to use one or the other, at different points in time; a clear shift which indicates that they are distinct mechanisms. People also use both within the course of making a single decision (Maule *et al.,* 2000).

While the argument that acceleration and filtration are distinct mechanisms has been supported, the distinction between these processes and what are considered in the literature to be the standard decision strategies (outlined in Chapter 1, Section 1.6) is more complex. This is due to the fact that filtration and acceleration are processes that form part of decision strategies. For example, many non-compensatory decision strategies are associated with filtration, or the concept of selectivity. Similarly, acceleration may also be representative of a decline in processing (specifically, a reduction in the amount of time spent per acquisition), which is one process associated with many non-compensatory strategies. As outlined in Chapter 1, Section 1.6, a decline in processing is not only visible through a reduction in the number of acquisitions made (Payne *et al.,* 1993) but also through depth of processing. Even though a proportionally equal number of information acquisitions may be made in the decision space, acceleration may involve a more superficial level of processing, where fewer trade-offs are made (Dhar & Nowlis, 1999; Payne *et al.,* 1993). Thus, the superficiality of processing, which may be associated with acceleration, can be representative of a decline in processing.

It has been suggested that acceleration and filtration may be considered, not just processes, but actual decision strategies in their own right (Dror, Busemeyer, & Basola, 1999). However, while acceleration and filtration are processes, decision strategies (barring random choice) are more complex and incorporate a variety of processes in their execution. Decision strategies focus more on how the information is considered (e.g. weightings), and the order in which is it considered (attribute vs. alternative driven search): they incorporate a variety of processes underlying decision making. However, because the processes of filtration and acceleration are single processes that are incorporated into a larger decision strategy, it can be hard to identify if decision makers are employing filtration, acceleration, or shifts in decision strategies under time pressure. Identification of the use of decision strategies, and not just the processes of filtration and acceleration, can be made more easily if there is evidence that filtration and acceleration are occurring simultaneously, or if other processes which contribute to the decision strategy (such as the pattern of processing) are identified.

Overall, there is considerable research which demonstrates that time pressure is not a completely negative factor for decision making; at mild/moderate levels, it leads to cognitive economy in terms of filtration, acceleration, or changes in decision strategies, which in turn encourages decision making by minimizing choice deferral (Dhar & Nowlis, 1999). These findings are consistent with E-Af (Payne *et al.,* 1993), which predicts that a sufficient, but not overwhelming, increase in task demand characterised by a mild/moderate level of time pressure results in a shift to more cognitively-economical information processing while maintaining relatively high levels of accuracy.
However, time pressure does not always result in the use of more efficient strategy changes, for several reasons. Increasing the computational load of the decision under time pressure can lead to a decline in performance. Goals that compete with cognitive economy, such as accuracy, can lead to maladaptive strategy use: decision makers may attempt to employ compensatory strategies that cannot be executed appropriately (Payne *et al.,* 1996; Zakay & Wooler, 1984).

In terms of stress, the Yerkes-Dodson principle predicts that, once a certain level of stress is reached, performance deteriorates. In decision making, once time pressure is too severe, decision makers tend to employ poor strategies. They either employ strategies available from habit that may not be best suited to the decision, employ poor-performing strategies such as random choice (RAN), or even avoid the decision (choice deferral or selection on the basis of a single outstanding attribute (Betsch, Fielder, & Brinkmann, 1998; Coombs, 1964; Janis & Mann, 1977; Payne *et al.*, 1993)). Some researchers argue that stress leads to hasty, disorganised, and incomplete processing (Janis, 1989; Janis & Mann, 1977). It has also been suggested that decision makers may not adopt different, more efficient strategies under time pressure, as the act of switching strategies might simply be too effortful in itself (Ordonez & Benson, 1997).

As demonstrated above, time pressure has been reported to have a range of both positive and negative effects on the decision making process. The fact that previous research has demonstrated such varied results may be due to the lack of consistency in the computational load of the decision spaces employed in these studies. The precise effects of time pressure are unclear, as additional variables relating to decision structure can be argued to confound the picture. Studies have employed a variety of decision scenarios (Alemi, 1986; Betsch *et al.,* 1998; Dhar & Nowlis, 1999; Dror *et al.*, 1999; Edland, 1994; Edland & Svenson, 1993; Joslyn & Hunt, 1998; Payne *et al.,* 1996; Wright, 1974), information (Diederich, 2003; Edland, 1994; Edland & Svenson, 1993; Franklin & Hunt, 1993; Maule *et al.*, 2000; Payne *et al.,* 1996; Wright, 1974), and even operationalisations of time pressure (Betsch *et al.*, 1998; Diederich, 2003; Dhar & Nowlis, 1993; Dror *et al.*, 1999; Edland & Svenson, 1993; Franklin & Hunt, 1993; Kerstholt, 1995; Maule *et al.*, 2000; Payne *et al.,* 1996; Ordonez & Benson, 1997; Wright, 1974). It is likely that each of the reported results is representative of a precise point in the hierarchy, where a specific computational demand (created by the specific operationalisation of decision and time pressure) is being handled by a specific amount of cognitive resources.

In order to obtain a clear picture of this hierarchy of adaptivity, a more structured study involving incremental increases in different aspects of the computational load should be conducted. Thus, the broad aim of this study was to take such an approach to examine the effect of mild/moderate time pressure in a clean, idealised 4x4 (4 attributes, 4 alternatives) decision space. The decision space was considered idealised as it was proportionally equal in terms of attributes and alternatives, of low complexity and made under conditions of certainty. Specifically, this study aimed to examine if and how cognitive streamlining occurred as a result of decision difficulty, and how similar or different these effects were to those observed in Study 1, as a result of decision complexity.

As in Study 1, Chapter 2, cognitive streamlining may be inferred from examination of the information acquisition process underlying decision making. The information acquisition process was measured by seven previously published measures relating to the amount of information processed, selectivity of search, and pattern of information acquisition. Any of the following would indicate shifts towards cognitive economy: decreases in the amount of information processed, increases in the selectivity of the search, or a change to a more attribute-led search pattern. If cognitive economy were evident on any of these measures, the secondary aim of this study was to consider the nature of this cognitive economy. In other words, an attempt was made to distinguish between the processes of acceleration, filtration, or changes in decision strategies. Acceleration will be judged by a decrease in the amount of time spent on each acquisition (while roughly the same proportion of information is acquired), while filtration is defined by an increase in selectivity of the search across attributes or alternatives. It should be relatively simple to distinguish acceleration and decision strategies from filtration; acceleration because it has been shown to be mutually exclusive from filtration; and decision strategies because, if a search is selective, it will also be reflected in the measures of the amount of processing. However, it is more difficult to distinguish between acceleration and a shift in decision strategies. As outlined in Chapter 1 and earlier in this chapter, every decision strategy is characterised by 3 distinct indices (amount of information processed, selectivity of search, and search pattern). The degree to which these are implemented differs not only across strategies, but within strategies in the face of different task demands. For example, an elimination by aspects (EBA; Tverksy, 1972) strategy involves processing less information more selectively, and has a more attribute-based search pattern than the weighted additive difference strategy, by definition. However, in the face of decisions of different computational demands, the extent of processing, selectivity, and degree of attribute-led pattern of serach of the EBA strategy will vary. A decline in the amount of processing may precede any increase in selectivity and processing (Payne *et al.*, 1993), and in the face of low computational demand may be the only process to change. Increased selectivity and attribute-driven processing, at least to the point where they can be measured, may only occur after a certain level of task demand has been reached, as was suggested in Study 1. Thus, while a clear indicator of shift in decision strategies can be judged by any combination of a decrease in processing, an increase in selectivity, or a shift to more attribute-led searching, it is possible that this shift will only be represented by a change to one of these factors. It may be possible to distinguish between acceleration and a shift in strategies, as acceleration predicts that the same amount of information will be processed, simply at a faster rate. The proportion of information examined within the decision space, therefore, may inform on the amount of information processed. However, it must be noted, as outlined above, that 'depth of processing' can not solely be measured by the proportion of information examined in the decision space. As such, this study also included a measure of ratio of acquisition time, to attempt to quantify 'depth of processing.' It is harder to distinguish between filtration and an increase in selectivity as part of a shift in decision strategy, but, as this thesis will argue, increases in selectivity are generally representative of a more significant shift towards cognitive economy, which follow decreases to the amount of information processed.

Table 3.1 Pattern of expected outcomes by theory of time pressure

Possible outcomes	**Anticipated results**
Acceleration	Decreased TperACQ, stable acquisition-time ratios
Filtration	Increased selectivity across attributes/alternatives
Shift in decision strategies	Any combination of: decreases in the amount of processing, increased selectivity, shift to attribute-led search patterns.

This study will also begin to examine the possible differential effects of demand source in increases in task demand. If time pressure can increase cognitive demand, as demonstrated by a trend to a more cognitively economical information acquisition process, in an 'idealised' decision space, this would provide support for the influence of external factors on the balance between task demand and task resources. This would suggest that, even when decision complexity (where the demand source stems from the decision itself) is low, decision difficulty may still be a critical factor in determining the task demand of a decision. How decision difficulty affects information acquisition, in comparison to decision complexity, will provide insights into the nature of these factors. If time pressure affects information acquisition differently to complexity, it may be concluded that they are different influences on the decision process. If time pressure produces identical changes in the information process as outlined in this study, it may be concluded either that they are similar mechanisms, or that decision makers do not distinguish between the source of increased task demand, only an absolute increase in it. It will also be interesting to determine if the effects of decision difficulty on the information acquisition process provide any additional support for the suggestion of a hierarchy of cognitive response to increasing task demands.

3.1 Method

3.1.1 Participants: The same 36 University of Southampton undergraduate participants (26 females, 10 males, age *M* 21, *SD* 2.81 years, range 18-35) who participated in Study 1, also participated in this study.

3.1.2 Stimuli/Procedure: Time pressure was operationalised by asking participants to complete the decision task as quickly as possible: it was emphasized that a rapid response time was critical. During the task, a clock face with a ticking second hand was present in the corner of the computer screen to reinforce the urgency message. This mechanism of operationalising time pressure, rather than a fixed time period, was selected for several reasons. First, no common operationalisation of time pressure has been adopted across previous studies in this area. Some studies define time pressure as the time it takes a participant to complete a task divided by 2; others as the task time divided by 3 (Edland, 1994; Edland & Svenson, 1993; Joslyn & Hunt, 1998; Wright, 1974). To do this, participants would have had to complete decision sets of equivalent sizes and domains to obtain a baseline measure, which would then have been halved. This would have resulted either in practice effects, or, if calculated actively on the session on the basis of the baseline condition, it would have restricted counterbalancing. It was felt that the technique of reinforcing the time pressure message verbally and visually rather than in a fixed manner, that has been successfully used in past studies (Dror et al., 1999), would create a subjective, but sufficiently equivalent across participants. At the end of the experimental session, participants were asked if they subjectively experienced time pressure, as a manipulation check. Thus, in the context of this thesis, decisions constituted of 16 items of information and no time pressure are defined as low task demand, and decision constituted of 16 items under time pressure are defined as high task demand.

3.1.3 Dependent measures: The dependent measures in this study were the same seven previously published measures as those in Studies 1 and 2; relating to amount of processing (TdTIME, ACQ, TperACQ, PTMI), selectivity (VARALT, VARATT), and pattern of search (PATTERN).

3.1.4 Analysis: The data analysis procedure followed that outlined in Study 1, except that, as the decisions in each condition were of equal size, proportionality between decisions was not considered. A manipulation check for time pressure was conducted by non-parametric analysis.

In addition to the analysis in the previous study, the ratio of acquisition time to deliberation time was calculated, to gain an insight into depth of processing rather than pure amount (number) of items processed. This was important as the acceleration theory of time pressure claims that roughly the same proportional amount of information in the decision space is processed (Ben Zur & Breznitz, 1981). The percentage of time spent on acquisition was calculated based on time spent on acquisitions (TperACQ x ACQ) divided by 1000, divided by total decision time, then multiplied by 100. The percentage of time spent on deliberation was considered to be time spent processing the information but not actively acquiring, or viewing, it: in other words, the remainder of the decision time, (TdTIME – ((TperACQ x ACQ)/1000) x 100.

With regard to the effects of demand source (difficulty vs. complexity), a main effect of decision type would be expected in decisions of different sizes. The complex decision and the difficult decision differ in size: 8x8 and 4x4 respectively. As such, it was expected that there would be significant differences in variables that are sensitive to decision space size; that is, those relating to the amount of processing. To examine any differences between the demand source (difficulty vs. complexity), any variables that are sensitive to decision size were considered proportionally. These variables include the majority of those which relate to the amount of processing: TdTIME, ACQ, and PTMI. Thus, to compare difficulty effects with those of complexity, ratio variables for these four measures were derived by dividing their value on the condition (8x8 or 4x4 time pressure) by their baseline 4x4 values. For example, the proportional TdTIME for the 8x8 condition was ((TdTIME 8x8)/ (TdTIME 4x4 baseline)), while the proportional TdTIME for the 4x4 time pressure condition was ((TdTIME 4x4 time pressure)/ (TdTIME 4x4 baseline)). A series of paired t-tests was then conducted on these ratio variables. Transforming these variables into ratio format enabled comparison of decision type, or demand source, effects while excluding decision size effects.

3.2 Results

A manipulation check for time pressure on a scale of 1 – 3 (1 = a lot, 2 = moderate, 3 = none) revealed that the median rating for this participant group was 2 (range 1 – 3), indicating that the group felt moderate time pressure in the time pressure condition.

All data were log transformed due to positive skew. Co-linearity of variables was not an issue, and thus all were analysed further (see Table 3.3). Table 3.2 contains raw score descriptives, for ease of interpretation.

3.2.1 The 4x4 condition:

As outlined in Study 1, Chapter 2.

Table 3.2 Mean dependent measures by decision condition

	4x4	4x4 time pressure
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	47.47 (36.02), 6.96 - 164.32	28.18 (29.91), 3.13 - 177.18
ACQ	35 (36.02), 6 - 132	25 (16.08), 5 - 68
TperACQ (ms)	524 (176.43), 180.60 – 957.50	417 (168.12), 167.80 - 843.60
PTMI	.31 (.13), .12 - .69	.29 (.16), .09 - 1.0
	Measures of selectivity	
VARALT	.017 (.016), .001 - .050	.019 (.032), .001 - .187
VARATT	.016 (.017), .001 - .081	.027 (.035), .001 - .187
	Measure of information acquisition	
PATTERN	.197 (.418), -.667 - 1.0	.175 (.477), -1.0 - 1.0
% acquisition time	37	37

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME x 100).

3.2.2 The 4x4 time pressure condition:

In the 4x4 time pressure condition, if every item were considered, the duration and number of acquisitions for each item would average at 1.8s and 1.6 respectively. If this is factored out in terms of alternatives, this would average out at 7.2s and 6.4 acquisitions per alternative. Participants spent, on average, 30% of the total decision time considering values of their subjectively determined most important attribute (PTMI). This was not significantly longer than expected if time were distributed equally across attributes (25%), $t(35) = 1.59, p = .120$. The pure measures of selectivity, VARATT and VARALT, implied a largely consistent search pattern as the variances are low (Payne *et al.*, 1988).

They were also not significantly different from each other, indicating no strong trend of selectivity towards attributes or alternatives, $t(35) = -1.76, p = .088$. In terms of PATTERN, the search appeared to be more alternative-led, compared to a consistent search value of 0, $t(35) = 2.20, p = .030$.

Table 3.3 Correlation matrix for dependent variables: 4x4 above the diagonal, 4x4 time pressure below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.59‡	.08	-.18	-.37 †	-.27	.21
ACQ	.61 ‡		.14	-.14	-.39 †	-.34 †	.06
TperACQ	.19	-.00		-.03	.17	.22	.11
PTMI	-.19	-.27	.29		.41 †	.22	-.36 †
VARATT	-.19	-.33	.11	.69 ‡		.56‡	-.06
VARALT	-.22	-.49 ‡	.41 †	.12	.30		-.03
PATTERN	.11	.16	.26	-.49 ‡	-.36 †	.08	

Note. † = $p < .05$ level (2 tailed); ‡ = $p < .01$ level (2 tailed)

3.2.3 A comparison of the 4x4 and 4x4 time pressure conditions:

In terms of the correlations between variables (see Table 3.3), there are consistencies in the pattern of correlations between the two conditions. As in the complexity conditions in Study 1, Chapter 2, TdTIME and ACQ were significantly positively correlated across both difficulty conditions. In addition, ACQ was negatively correlated with VARALT for both conditions, indicating that fewer acquisitions are associated with higher selectively across alternatives. Across conditions, PATTERN was negatively correlated with PTMI, which indicates the longer time was spent in the subjectively most important attribute, the more non-compensatory the search, which is consistent with the predictions of adaptive decision making and the shift to non-compensatory processing.

In terms of differences in correlation patterns between the conditions, ACQ was significantly negatively correlated with VARATT in the low difficulty condition, and in this condition, VARATT and VARALT were positively correlated, implying that any selectivity that occurred, occurred across both attributes and alternatives. This was not the case in the high difficulty condition. In the high difficulty condition, PTMI and VARATT were significantly positively correlated, indicating that the more time that was spent in the subjectively most important attribute, the most selective the search across attributes.

A repeated measures MANOVA of difficulty (4x4, 4x4 time pressure) for the transformed dependent variables (TdTIME, ACQ, TperACQ, PTMI, VARALT, VARATT, PATTERN) revealed an overall effect of time pressure, $F(7, 28) = 3.6, p = .005$. Specifically, there were significant effects of difficulty in TdTIME, $F(1, 35) = 20.8, p < .001$, in ACQ, $F(1, 35) = 14.8, p < .001$, and in TperACQ, $F(1, 35) = 9.4,\ p = .004$. Thus, under time pressure, participants took significantly less time to make their decisions, made fewer acquisitions, and spent less time on each acquisition.

No significant effects for difficulty were found for PTMI, $F(1, 35) = .73,\ p = .400$, VARATT, $F(1, 35) = .87,\ p = .358$, VARALT, $F(1, 35) = .41,\ p = .529$, and PATTERN, $F(1, 35) = .09,\ p = .759$. Thus, participants were no more selective in their information acquisition, and did not change their search pattern to a more non-compensatory attribute-led pattern under time pressure. The ratio of acquisition time to deliberation time was not significantly different across conditions, $t(35) = 0.75$, p = .460.

3.2.4 A comparison of the difficulty (4x4 time pressure) and complexity (8x8) conditions:

To account for decision size differences, variables relating to the amount of processing which are susceptible to decision size (TdTIME, ACQ, PTMI) for both difficulty (4x4 time pressure) and complexity (8x8) conditions were transformed into ratio values in terms of their baseline 4x4 values (see Table 3.4). A series of paired t-tests for these transformed values revealed significant differences in computational type (complexity vs. difficulty) for TdTIME, $t(35) = 4.76, p < .001$, ACQ, $t(35) = 5.72, p < .001$, and PTMI, $t(35) = -3.1, p = .004$.

Table 3.4 Transformed ratio values for amount of processing measures

	4x4 time pressure	8x8
	Ratio measures of information processing	
	M (*SD*)[1]	*M* (*SD*)
rTdTime (s)	.76 (.85)	1.88 (1.16)
rACQ	.80 (.37)	2.06 (1.32)
rPTMI	1.08 (.75)	.75 (.51)

Note. rTdTime = total time to decision ratio; rACQ= ratio of number of information boxes examined; rTperACQ = time per information acquisition ratio; rPTMI = ratio of proportion of time spent on subjectively most important attribute

It is important to note that the values in Table 3.4 are ratio values, in relation to the baseline values for the 4x4 condition. Therefore, a larger increase from the baseline value will result in a larger ratio value. Thus, complexity as the demand source led to a significantly longer average total decision time, and a significantly greater number of acquisitions. In addition, complexity resulted in a significantly lower proportion of time spent on the subjectively most important attribute, compared to difficulty. This implies that decision makers considered a number of attributes available to them, rather than focusing on their subjectively most important variable. Overall, this indicates a greater amount of processing occurred in the complex decision, compared to the difficult decision. However, a note of caution must be made, in that it is difficult to completely eliminate decision size effects from this analysis.

[1] Proportions were calculated for each individual and then averaged rather than calculated from condition averages.

A repeated measures MANOVA of decision type (4x4 difficulty, 8x8 complexity) for the transformed dependent variables that were not susceptible to decision size effects (TperACQ, VARALT, VARATT) and PATTERN revealed no overall effect of decision type, $F(4,32) = 1.88, p = .139$. There was a significant effect of decision type, or demand source, on TperACQ, $F(1,35) = 4.78, p = .033$. There were no significant effects of decision type for VARATT, $F(1,35) = 1.13, p = .296$; VARALT, $F(1,35) = .12, p = .734$; or PATTERN, $F(1,35) = 2.86, p = .100$. Participants did not differ in the selectivity or type of search pattern, in the face of different demand sources.

3.3 Discussion

This study set out to examine the effects of increasing decision difficulty (operationalised by time pressure) in an idealised decision space, on the process of information acquisition underlying decision making. Specifically, the aims were to examine if there was support for any of the three main theories of the effects of mild/moderate time pressure on information acquisition in decision making: acceleration, filtration, or a shift in decision strategies. A final study aim was to compare the results of this study with those of Study 1, Chapter 2: in effect comparing the difference between decision complexity and decision difficulty on information acquisition.

The results of this study demonstrate that time pressure led to cognitive streamlining, in terms of the amount of information processed. Under time pressure, on average, participants made significantly fewer acquisitions, spent significantly less time on each acquisition, and as such, the overall decision time was significantly less than the decision time in the no time pressure condition. In fact, on average, participants made fewer than half the number of acquisitions for half the amount of time per acquisition on the time pressure condition, compared to the no time pressure condition. Acceleration in previous studies has been linked to a decrease in the average time per information acquisition (Ben Zur & Breznitz, 1981, Payne *et al.*, 1988). The results of this study lend support to the theory of acceleration. However, Ben Zur & Breznitz (1981) also specify that acceleration involves the processing of roughly the same amount of information in the decision space, in terms of the proportion of information available. Despite the decline in the number of ACQs in the time pressure condition, it can be argued that an equivalent proportion of the information available in the decision space was being processed in the time pressure condition compared to the no time pressure condition for several reasons. First, it is likely that each item in the decision space was considered at least once as the number of acquisitions in each condition exceeded the number of items available in the decision space. Even if each item were not considered, the fact that there were repetitions implied that the participants had ample opportunity to process the information that they wished to acquire. Second, the ratio of acquisition time to deliberation time was equivalent across conditions. This suggests that roughly the same proportion of information in the decision space was considered for a similar proportion of time. This is consistent with the theory of acceleration (Ben Zur & Breznitz, 1961). However, while the same proportion of information was considered, it may be argued that the overall information processing load did decline. Each item was acquired less often than it was in absence of time pressure, (i.e. there was less repetition), and each item was considered for less time. Arguably, despite an equivalent acquisition ratio across conditions, both of these factors indicate that the depth of processing declined under time pressure, which is consistent both with findings that time pressure leads to less scrutiny of each information acquisition (Edland & Svenson, 1993), and the theoretical predictions that non-compensatory decision strategies result in a decrease in information processing (Payne *et al.,* 1993). Thus, it is argued that the results of this study suggest a decline in the amount of information processed in the time pressure condition, in terms of depth of processing, and as such a shift of decision strategies (which include acceleration of processing as part of the strategies adopted) cannot be excluded as the underlying cause to changes in information acquisition.

While it appears that acceleration of processing occurred in response to time pressure, there is no evidence for filtration (Miller, 1960), as there was an absence of increased selectivity in the time pressure condition. In addition, there was no obvious evidence for a trend towards more attribute-based processing as a result of time pressure. As outlined earlier, it can be hard to distinguish between single processes such as acceleration and decision strategies that include, but are not restricted to, a single process. Thus, while the absence of increased selectivity and attribute-based processing does not indicate the use of decision strategies, nor does it exclude the possibility that change in decision strategy underlay the cognitive streamlining found in this study. As was suggested in Study 1, Chapter 2, changes in decision strategy selection may not always be evident through changes in selectivity or pattern measures. The decrease in processing that is evident may or may not be indicative of a shift to more non-compensatory decision strategies, but as in Study 1, the level of task demand induced in this study may not be sufficient to translate to changes in the selectivity and pattern of the search. It is possible that the hierarchy of adaptivity may commence earlier than Payne *et al.* (1988) suggested. Rather than decision strategies being modified only under severe time pressure, it is possible that they shift under mild/moderate pressure, but that this is only visible through a decrease in information processing. It may be that more severe time pressure, or diminished resources in the face of equivalent time pressure, results in the adoption of more severely non-compensatory strategies, which are characterised by increased selectivity and attribute-led processing. This gradient, or continuum of effort within decision strategies, was never made explicit by Payne *et al.* This concept of a hierarchy of adaptivity based on a shift between and within strategies will be explored further in Chapter 5, where it will be examined where effects of time pressure are exacerbated in a population with diminished cognitive resources.

This study also aimed to compare the effects of decision difficulty, operationalised in this study by time pressure, with decision complexity, operationalised in Study 1, Chapter 2, by a proportional increase in decision space size. Both decision complexity and decision difficulty led to cognitive streamlining; however, there are some differences between the two in the nature of this streamlining. The first difference between them is that decision difficulty led to accelerated processing, in terms of a reduction in the amount of time spent on each acquisition, while decision complexity did not. The second difference is that the relative decline in the amount of information processed due to decision complexity was arguably less than the decline due to decision difficulty, in terms of ratio values. In terms of a basic comparison of changes to information acquisition as a result of increased complexity and difficulty, it is clear that participants responded differently to different demand sources. This is important, as the E-Af has always quantified task demand as a unitary concept, based on a pure measure of quantity, and did not account for qualitative differences in terms of source. The results of the previous two studies suggest that demand source must be considered when considering task demand, and thus it is suggested that the E-Af should be modified to this effect.

In summary, this study provides results that are consistent with most of the predictions of the E-Af, in that cognitive economy was adopted as task demand increased. This study also provides support for the differences in demand source; the cause, and not simply the amount, of the increased demand may influence the information acquisition process more than previously thought. Broadly, the differential response in the degree and nature of cognitive streamlining in the face of different types of computational demand provides support for the concept of a hierarchy of adaptivity. Through comparison between this and the previous study, it is clear that the information acquisition process underlying decision making differed in response to the task demand sources of complexity and difficulty. The diverse types of cognitive streamlining adopted in the face of decision complexity and decision difficulty may also enable inferences about the nature of computational demand which stems from either increased difficulty or complexity. On the other hand, the decision complexity and difficulty decisions in this research program may simply represent different degrees of computational load, and the provenance of that load is irrelevant. Further research is necessary to determine precisely how computational demand can be measured across different sources, and if these sources play a more influential role than an absolute increase or decrease in cognitive load.

This study is inconsistent with previous research, which has demonstrated clear support for one of the three main theories of cognitive economy due to time pressure. This may be due to methodological differences. As suggested in Study 1, Chapter 2, and in the introduction to this chapter, it is more likely that the 'idealised' nature of the decision space is accountable for the inconsistency of these results with past research. The decision space in this study was neutral in terms of attractiveness of alternatives. Previous studies have manipulated, or failed to hold constant, the relative attractiveness of alternatives, despite the fact that it has been found to be strongly correlated with time pressure in past studies (Ben Zur & Breznitz, 1981; Canavan, 1969; Edland, 1994; Wright, 1974; Webster, 1964).

Previous time pressure studies have tended to use decision spaces which involve risk, uncertainty, or which are disproportionate in size (Ben Zur & Breznitz, 1981, Miller, 1960; Payne *et al.*, 1996; Payne *et al.*, 1988, Payne *et al.*, 1993; Svenson & Edland, 1993; Wright, 1974). Uncertainty and risk are linked to stress, which may also have exacerbated the effects of time pressure. As the decision space in this study did not link to risk or uncertainty, the moderate time pressure that participants reported may not have translated into physiological stress. In turn, they may not have experienced a change in affect that has been suggested to be the true influencing factor underlying time pressure effects (Maule *et al.,* 2000). Thus, due to the nature of the decision space, this study may not have reached an equivalent level of task demand as that reached in previous studies. As such, the more severe cognitive streamlining reported in other studies would not be expected here.

The very fact that such different responses, in terms of cognitive economy, are seen across the range of task demands in other research is even stronger evidence that decision makers are adaptive. It can be inferred that, on some level, decision makers are making the effort to match the precise level of task demand with the necessary amount of computational effort. This hierarchy of adaptivity mitigates the response to changes in the balance between task resources and task demand, possibly first through decreases in processing, then in increased selectivity and more attribute-based searches (Payne *et al.,* 1993). However, as mentioned in the introduction to this chapter, research into different aspects of the computational load should be conducted in a structured program of incremental increases in computational demand. The studies reported in this thesis are only the first step in such an endeavour.

The possible criticisms of the measures used in Study 1, Chapter 2, will also apply here. This study provides another example that, perhaps, the dependent measures that are traditionally used are not comprehensive or sensitive enough to distinguish between decision strategies or mechanisms such as acceleration and filtration. For example, additional measures such as the overall proportion of information considered would be useful to aid in distinguishing between acceleration and a simple decrease in the amount of information processed.

It must be noted that all time pressure studies conducted in laboratory settings have been criticised for lacking ecological validity. Franklin & Hunt (1993) contend that the very nature of time pressure makes it impossible to replicate in the lab. They suggest that a time pressure situation must involve significant personal consequences as a result of choosing one option over another. Although this is more representative of outcome pressure, it may be an important part of real life time pressure decision making that is not viewed in laboratory studies. Kerstholt (1995) argues that it is impossible to study time pressure decision making in a static environment; a feature of most lab studies. He concedes that time pressure may be studied in controlled conditions, but maintains that for time pressure to be tested in a lab you need a dynamic task involving a simulated system that can be controlled over some period of time. A critical part of a dynamic environment is the availability of feedback, to enable the decision maker to view the overall state of the system and affect it. Dynamic decisions are also made in real time. Kerstholt (1995) also argues that time pressure in a static environment is merely a restriction, while in a dynamic one it is positively correlated to negative feelings. As such, time pressure as operationalised in this study may be missing key features of real-world time pressure, such as feedback and negative affect, which other studies have included.

The results of this study are arguably more valuable given some of the criticisms mentioned above. The fact that clear cognitive streamlining occurred in such an idealised, low-ecologically valid environment demonstrates that time pressure is a powerful determinant of task demand, and as such has great influence on the information acquisition process underlying decision making. In a more complex environment with more variables, more information about existing variables, active feedback, and potentially negative affect (Kersthölt, 1995), it is likely that the cognitive streamlining effects reported here would be exacerbated. The very fact that researchers have reported such varied responses to time pressure provides further insight in to the nature of the balance between task demand and cognitive resources, and lends support to the concept of a hierarchy of adaptivity.

In the last two studies, the effects of an imbalance between task demands and computational resources available for that task have been studied, through the manipulation of task demand. This was first achieved by increasing decision complexity, and subsequently by increasing decision difficulty. The next two studies will report the effects of increasing the mismatch between task demands and task resources on information acquisition. Task demand will be manipulated by the same means as Studies 1 and 2 (Chapters 2 and 3), but the amount of resources available for that task will also be quasi-manipulated. The latter will be operationalised in Studies 3 and 4, Chapters 4 and 5 by an older participant group, as cognitive resources have been repeatedly demonstrated to decline in older age (Kemper, 1994; Park & Schwartz, 2000).

Chapter 4.

Study 3: The influence of increased decision complexity and reduced cognitive resources on the information acquisition process underlying decision making

4.0 Introduction

It is proposed that the balance between task demands and the cognitive resources available for the task influences the information acquisition process underlying decision making. According to the Effort-Accuracy framework (E-Af; Payne, Bettman, & Johnson, 1993), as task demand increases, and computational levels are stretched, decision makers shift to more cognitively-economical information processing at the varying expense of decision accuracy.

As previously outlined, task demand is determined in part by decision complexity, which contributes to the computational demand of a decision. The former is defined by the number of attributes and alternatives in the decision space (Hogarth, 1975; Payne, 1976, 1982). Cognitively economical processing is defined by a reduction in the amount of information processed, an increase in processing of subjectively important information, and a more attribute-led search pattern across the decision space. In Study 1, Chapter 2, the effect of increasing decision complexity in a population of young adults was examined. In the face of increased decision complexity, this population of decision makers demonstrated cognitive streamlining, specifically in a reduction (both absolute and relative) in the amount of information processed. However, there was no evidence for increased selectivity or attribute-led search patterns.

It was proposed that this may represent a hierarchy of adaptivity, which is thought to represent differential cognitive economizing contingent on specific levels of task demand. Mild/moderate demand may result in initial reductions in computational expenditure, which is represented by a decline in the amount of information processed.

More severe levels of task demand may lead to greater degrees of cognitive economy, represented by selectivity and an attribute-led pattern of search (Payne *et al.*, 1993).

In Study 1, Chapter 2, only the level of task demand, to mild/moderate degrees, was manipulated in the face of stable, optimal levels of cognitive resources (why the resource levels may be considered optimal will be discussed shortly). By contrast, the aim of this study was to examine the effects of a greater discrepancy between task demands and cognitive resources on the information acquisition process. As well as manipulating the level of decision complexity, as in Study 1, the level of cognitive resources available to apply to the situation differed between participant groups. A quasi- experimental manipulation of the level of cognitive resources available to apply to the decision was operationalised by the participant population in this study: older adults. The broad aim of this study was to examine how older age affects the information acquisition process, in a low complexity (4x4) decision and a high complexity (8x8) decision. These results will be compared to those of the young population in Study 1.

The ageing process has consistently been shown to be related to cognitive decline which begins in the mid-20s (Kemper, 1994; Park & Schwartz, 2000). Considerable work has linked age-related cognitive decline to physical changes in the brain (McGreer, McGreer, & Suzuki, 1977; Park, Polk, Mikels, Taylor, & Marshuetz, 2001; Peters, 1996; Raz, 2000, 2004; Raz, Gunning, Head, Dupuis, McQuain, Briggs, Loken, Thornton, & Acker, 1997; Soininen, Puranen, Helkala, Laakso, & Riekkinen, 1992; Sullivan, Marsh, Mathalon, Lim, & Pfefferbaum, 1995; see Raz (2004) and Stern (2003) for reviews).

Cognitively, age has a well-documented, negative impact on fluid intellectual abilities, such as processing speed, working memory, recall, executive function (dual task performance), and attention (Bäckman, Small, Wahlin, & Larsson, 1999; Craik, 1977; Craik & Jennings, 1992; Craik & McDowd, 1987; Holtzer, Stern, & Rakitin, 2004; Maciokas & Crognale, 2003; Schaie & Willis, 1996; Park & Shaw, 1992; Rogers, 2000; Zacks & Hasher, 1997). In contrast, crystallised intelligence (functions such as vocabulary) remains unaffected or even improves with age (Horn, 1982; Horn & Hofer, 1992; Schaie, 1994).

Of particular relevance to this thesis are the well-documented, age-related declines in working memory and attention (Craik & Byrd, 1982; Light, 2000; Verhaeghen, Marcoen, & Goossens, 1993), which, arguably, represent an age-related decline in cognitive resources (Charness, 1985; Craik & Salthouse, 2000; Craik, 1986; Park & Schwartz, 2000; Reese & Rodeheaver, 1985). Specifically, in comparison to younger adults, older adults process information more slowly (e.g. Birren, 1965; Birren, Woods, & Williams, 1980; Cerella, 1985); are less able to ignore irrelevant information (Hasher & Zacks, 1988); are less able to manipulate items in working memory (Babcock & Salthouse, 1991; Wingfield, Stine, Lahar, & Aberdeen, 1988); and have more difficulty shifting and mentally manipulating information (Dror, Schmitz-Williams, & Smith, 2005). All of these findings have direct impact on working memory capabilities. Van der Linden, Hupert, Feyereisen, Schelstraete, Bestgen, Bruyer, Lories, Abdessadek and Seron (1999) argue that the construct of working memory should retain a principle role in explanations of age-related differences, although they agree that speed of processing is also an influential factor. A decline in the latter can also be considered to be representative of diminished cognitive resources, in the sense that cognition is less efficient.

The cognitive effect of ageing on decision making is an under-researched area of study (Peters, Finucane, MacGregor, & Slovic, 2000), despite the fact that the ability to make good decisions is critical to people's quality of life and longevity (Sanfey & Hastie, 1999). Specifically, very few studies have examined the effects of ageing on the information acquisition process underlying decision making. From an 'everyday' problem solving perspective, research has revealed that the tendency to rely on heuristic information processing increases with age, and older adults are reported to rely more on efficient processes in decision making (Park, 1999).

Specifically in terms of the information acquisition search pattern, there is evidence to suggest that older adults engage in more systematic, less redundant searches than their younger, equally-skilled counterparts (Charness, 1981b; Johnson & Drungle, 2000). Johnson (1990) supported these findings, demonstrating that older adults recheck decision space information less than younger adults. Older adults have also been shown to be more selective with regard to information processing than younger adults (Meyer, Russo, & Talbot, 1995; Riggle & Johnson, 1996; Walsh & Hershey, 1993; Zwahr, Park, & Shifren, 1999), and in the type of information they consider (Rafaely, Dror, & Remington, 2006). In addition to acquiring less information, older adults have been shown to take longer to consider the information and to reach a decision (Johnson, 1990; Johnson, Schmitt, & Pietrukowicz, 1989; Riggle & Johnson, 1996). There is also a suggestion that older adults engage in more non-compensatory decision strategies (Johnson, 1990). Recently, Mata, Schooler, & Rieskamp (2007) demonstrated that older adults do look up less information and take longer to process it, and use simpler, less cognitively demanding strategies to acquire this information. Measures of fluid intelligence accounted for age-related differences in information search and strategy selection, which is consistent with age-related declines in cognition. However, even thought older adults tended to employ simpler strategies, both young and older adults seem to be equally adapted decision makers in that they adjust their information search and strategy selection as a function of environment structure (or task demand). There is also evidence that decision makers of different ages recognise that different factors underlie their decision making (de Acedo Lizarraga, de Acedo Baquedano, & Cardelle-Elawar, 2007).

Generally, these findings provide evidence for age-related cognitive streamlining (Klaczynski & Robinson, 2000). However, these studies have largely been based on self-report protocols or paper and pencil-based observations: none has employed a precise process tracing system, such as Mouselab, to record the information acquisition process. Mouselab ensures that all information acquired is recorded; a factor that may be lost in self-report methodologies. In addition, Mouselab is a system that enables accurate and standardised measurement of acquisition times and selectivity variables, which enables comparison across populations in future studies. Furthermore, all of the studies outlined above have focused on how older adults differ with respect to younger adults: none of these studies has examined interaction effects between ageing and changing task demands.

This aim of this study was not only to explore age-related differences in decision making, specifically how older adults compare to younger adults in terms of the information acquisition process, but also to examine if and how older adults adapt to increasing levels of task demand. The broader aim of this study was further to examine the hierarchy of adaptivity first proposed in Chapter 2. This study was a replication of Study 1, Chapter 2, but employed an older adult participant population to increase the mismatch between task demands and cognitive resources. As in Study 1, cognitive effort was measured in terms of the dependent measures employed in the previous studies: the amount of information processed, the selectivity of the search, and the pattern of the information acquisition process.

Thus, effects of ageing on the information acquisition process under conditions of low (4x4) and high (8x8) decision complexity were examined. According to the E-Af (Payne *et al.*, 1993), age-related cognitive declines should lead older adults to experience a mismatch between resources and task demand at an earlier point than younger adults. As such, the effects of increasing task demand in the form of increasing decision complexity (namely a shift to cognitive streamlining) should be exacerbated in older adults. In addition, older adults are more experienced in decision making, and are accustomed to employing decision heuristics (Poon & Siegler, 1991; Takagi, 1997; Viggiano, Righi, & Galli, 2005). Both of these factors suggest older adults will exhibit more cognitive streamlining than younger adults on equivalent decisions. It is also possible that older adults may experience cognitive strain in the low complexity condition.

However, rather than leading to increased efficiency, it is possible that ageing may lead to a computational breakdown in decision making, as a result of cognitive limitations and/or experience. In terms of cognitive limitations, older adults may surpass the critical point in performance (outlined in the Yerks-Dodson principle in the previous chapter) earlier than younger adults; they may simply be completely overloaded by the task demand. As such, they may apply poor decision strategies that involve no computational effort, such as single attribute or random choice (RAN).

Table 4.1 Possible outcomes and contributing factors

Possible outcomes	Possible contributing factors
+ Cognitive streamlining, increased efficiency	1. natural adaptivity: shift to non-compensatory strategies 2. shifts in knowledge structures change information processing
- Cognitive overload, breakdown in efficiency, poor strategy selection	1. adaptivity failure: cognitive system cannot conduct any organised search 2. habitual strategy usage leads to inappropriate strategy selection

In terms of the putative negative consequences of experience, it is possible that older adults will be bound by habit, and that by force of habit they may maladaptively apply certain strategies to novel decisions (Payne *et al.*, 1993). Cognitive overload may also be evident through a hasty, disorganised search pattern (Janis, 1989). Thus, cognitive overload may lead to a complete breakdown in efficiency, visible in a lack of any cognitive streamlining, or the misapplication of strategies.

4.1 Method

4.1.1 Participants: This study used a within-participants design. Thirty six (22 females, 14 males, *M* 71.5 years, *SD* 6.9) older adults volunteered to participate. They all judged themselves to be computer-literate and comfortable with this technology. As the concept of cognitive capacity is critical to this study, all participants were administered a standardized test of working memory (Digits Backward, a subtest in the WAIS- III, Wechsler, 1997). This sample of older adults had an average digit span score of 6.0 (*SD* 1.3), with a range across participants between 4 and 8 items. From this, an average working memory capacity of 6 items can be inferred for the older group. This compares to an average digit span score, and hence average working memory capacity, of 7.2 for the young adult group. The average working memory span for the older adult group was significantly lower than that of the younger adult group, $t(72) = 2.79, p = .007$.

4.1.2 Stimuli/Procedure: The procedure followed was identical to that of Study 1, except that older adults were given the option between a regular mouse and an ergonomic, anti-arthritis mouse. No one selected the latter.

4.1.3 Dependent measures: In this study, the seven previously published measures that were used in previous studies were used: relating to amount of processing (TdTIME, ACQ, TperACQ, PTMI), selectivity (VARALT, VARATT), and pattern of search (PATTERN).

4.1.4 Analysis: The data analysis procedure followed that outlined in Study 1, Chapter 2. Also, to compare older and younger decision makers, a repeated measures MANOVA of complexity and age group was conducted on the transformed variables. A series of non-parametric tests, between and within age groups, was conducted to explore any interactions.

4.2 Results

All data were log transformed due to positive skew. There were no issues of co-linearity between dependent variables (see Table 4.3). Tables 4.2, 4.4, and 4.5 contain raw score descriptives, for ease of interpretation.

4.2.1 4x4 condition

If all items of information in the decision space were considered, this would average at 3.7s and 1.3 acquisitions per item. Factored out by alternative, this would average at 14.6s and 5 acquisitions per alternative. In a 16 item decision space, with 4 attributes in each alternative, this implies just over one acquisition per item, which in turn implies a low rate of repetition of acquisitions. The average amount of time per acquisition was quite high, at an average of more than one second for each acquisition.

Table 4.2 Mean dependent measures by decision condition

	4x4	8x8
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	58.55 (69.70), 6.34 – 322.37	102.12 (79.11), 1.32 - 396.31
ACQ	20 (23.0), 1 - 47	38 (26.6), 2 - 109
TperACQ (ms)	1136 (719.32), 311.60 – 3723.90	1214 (779.22), 281.10 - 3714.0
PTMI	.37 (.24), 0 – 1.0	.28 (.25), 0 - 1.0
	Measures of selectivity	
VARALT	.040 (.050), .001 - .187	.025 (.022), .001 - .110
VARATT	.036 (.049), .001 - .187	.027 (.036), .001 - .120
	Measure of information acquisition	
PATTERN	-.019(.505), -1.0 - 1.0	-.028 (.537), -1.0 - 1.0

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

Participants spent on average 37% of the time on the subjectively most important attribute (PTMI), which was significantly more than the 25% of the time they should have spent if processing were equivalent across the 4 attributes, $t(35) = -593.47, p < .001$. In terms of information processing, the demands appeared to be moderate, with few acquisitions taking a considerable amount of time, and evidence of selectivity of processing.

In terms of selectivity of the search pattern, this appeared to be highly selective across attributes, and moderately so across alternatives (Payne, Bettman, & Johnson, 1988). The information acquisition pattern was neither significantly attribute nor alternative-led, compared to a neutral search pattern value of 0, $t(35) = -.23, p = .820$.

Table 4.3 Correlation matrix for dependent variables: 4x4 above the diagonal, 8x8 below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.68‡	.35†	-.16	-.28	-.31	.24
ACQ	.65 ‡		-.18	-.27	-.54 ‡	-.54 ‡	.35†
TperACQ	.17	-.33		.21	.30	.20	.15
PTMI	-.23	-.21	.10		.78 ‡	.32	-.24
VARATT	-.47‡	-.57 ‡	.14	.60‡		.57‡	-.21
VARALT	-.15	-.44 ‡	.49‡	-.23	.25		-.28
PATTERN	.41†	.33†	.12	-.52‡	-.58‡	.13	

Note. † = p <.05 level (2 tailed); ‡ = p < .01 level (2 tailed)

4.2.2 8x8 condition

In the 8x8 condition, if every item were considered, this would average at 1.6s and 0.6 acquisitions per item. Across alternatives, this would average at 12.8s and 4.7 acquisitions. This implies that only half of the available information in the decision space was considered in this decision, and that each acquisition took on average more than one second. Participants spent 28% of the time considering information in their subjectively most important attribute (PTMI), which is significantly different to the 12.5% of the time they would have spent if processing demands were consistent across attributes, $t(35) = -287.79, p < .001$. In terms of information processing, the demand appears to be high: participants did not able to process information about all items in the decision space, but needed a considerable amount of time to process each acquisition that was made. In addition, there was evidence for moderate selectivity of processing across attributes and alternatives (Payne *et al.*, 1988). In terms of PATTERN, the search was not significantly attribute-led, compared to a neutral search pattern value of 0, $t(35) = -.32, p = .750$.

4.2.3 A comparison of the 4x4 and 8x8 conditions

In terms of the pattern of correlation between the two conditions (see Table 4.3), there are a number of consistencies between the low and high complexity conditions for the older adult group. TdTIME and ACQ were positively correlated in both conditions, as seen in the previous studies relating to the younger adults. In addition, VARATT and VARALT were negatively correlated with the number of acquisitions made, implying that a more selective search resulted in fewer acquisitions – an indication of efficiency of search. PTMI was also positively correlated with VARATT across conditions, which implies that the proportion of time spent in the most important attribute was relatively much greater than the time spent across remaining attributes. Across conditions, PATTERN was significantly positively correlated with the number of acquisitions made, which indicates that, if the search was more compensatory (i.e. more alternative-led), more acquisitions were made, as the theory of adaptive decision making would predict.

There were also differences in the pattern of correlations across conditions, particularly relating to the PATTERN variable. In the high complexity condition, there was a high positive correlation between TdTIME and PATTERN, indicating that the more compensatory searches took more time. In addition, PTMI and PATTERN were significantly negatively correlated, indicating that when PATTERN was lower (i.e. a more non-compensatory search), PTMI was higher (i.e. more time was spent on the most important attributes). Both of these suggest that the high complexity condition resulted in more cognitive streamlining that the low complexity condition.

A repeated measures MANOVA of complexity was carried out for the transformed variables (TdTIME, ACQ, TperACQ, PTMI, VARALT, VARATT, PATTERN) and revealed a main effect of complexity, $F(7, 28) = 20.34, p < .001$. Specifically, it revealed significant effects of complexity in TdTIME, $F(1, 35) = 24.07, p < .001$, ACQ, $F(1, 35) = 36.95, p < .001$, PTMI, $F(1, 35) = 12.97, p = .001$, and PATTERN, $F(1, 35) = 4.77, p = .036$. No significant effects for complexity were found in TperACQ, $F(1, 35) = .99, p = .327$, VARATT, $F(1, 35) = 1.63, p = .210$, or VARALT, $F(1, 35) = .50, p = .482$. There was significant deviation from normality for the residuals of 5 variables, two from the 4x4 condition (ACQ and PATTERN) and three from the 8x8 condition (TdTIME, ACQ, PATTERN). As in the MANOVA, there were consistently significant effects of complexity on TdTIME, $Z(N{=}36) = -4.12, p < .001$, ACQ, $Z(N{=}36) = -4.38, p < .001$, PTMI, $Z(N{=}36) = -2.89, p = .004$, and PATTERN, $Z(N{=}36) = -2.13, p = .033$. There were consistently no effects of complexity on TperACQ, $Z(N=36) = -.89$, $p = .371$, VARATT, $Z(N=36) = -1.37$, $p = .169$, or VARALT, $Z(N=36) = -.66$, $p = .512$.

However, as in Study 1, Chapter 2, proportionality between conditions for TdTIME, ACQ, and PTMI must be considered. Given the baseline TdTIME of this group for the 4x4 condition, this would predict a TdTIME of 234.2s on the 8x8 condition, if processing demands were maintained across conditions. In fact, TdTIME in the 8x8 condition was significantly less than this, at 102.1s, $t(35) = 3019.29$, $p < .001$. Similarly, the actual number of acquisitions on the 8x8 condition was significantly less than the predicted value of 80 (4 x ACQ4), $t(35) = 1170.20$, $p < .001$. In terms of PTMI in the 4x4 condition, participants spent 12% more time in their subjectively most important attribute than an equal division of attention across attributes would predict (25 % = 100%/4).. In the 8x8 condition, participants spent 13.5% more time in the PTMI than they would have if processing demands had been equal across all 8 attributes. So, while the first analysis appeared to suggest that selectivity was greater in the 4x4 condition, when proportionality was considered, PTMI across conditions was approximately equal. Thus, participants appeared to process proportionately less information in the 8x8 condition than the computational demand of the 4x4 condition would predict, but did not appear to become more selective in terms of subjective preference in examining attributes.

4.2.4 A comparison of the 4x4 and 8x8 conditions across age groups

A repeated measures MANOVA of complexity (4x4, 8x8) by age group (young, older) for the transformed dependent variables (TdTIME, ACQ, TperACQ, PTMI, VARALT, VARATT, PATTERN) revealed a main effect of complexity $F(7, 64) = 27.98$, $p < .001$. This arose through effects in TdTIME, $F(1, 70) = 38.27$, $p < .001$, ACQ, $F(1,70) = 81.27$, $p < .001$, PTMI, $F(1, 70) = 81.59$, $p < .001$, and VARATT, $F(1, 70) = 4.57$, $p = .036$. There were also main effects of age, for ACQ, $F(1, 70) = 14.49$, $p < .001$, TperACQ, $F(1, 70) = 49.25$, $p < .001$, PTMI, $F(1, 70) = 49.75$, $p < .001$, VARATT, $F(1, 70) = .6.62$ $p = .012$, and VARALT, $F(1, 70) = 7.49$, $p = .008$. There was significant deviation from normality for the residuals of 6 variables (ACQ4, ACQ8, TperACQ8, PTMI8, VARATT8, and VARALT8). There were significant effects for age group in

ACQ4, $Z(N=72) = -3.04, p = .002$, ACQ8, $Z(N=72) = -2.98, p = .002$, TperACQ4, $Z(N=72) = -4.98, p < .001$, TperACQ8, $Z(N=72) = -5.72, p < .001$, PTMI8, $Z(N=72) = -6.95, p < .001$, VARATT8, $Z(N=72) = -2.82, p = .005$, and VARALT4, $Z(N=72) = -2.48$, $p = .013$.

Table 4.4 Mean dependent measures by age group for the 4x4 decision

	Older	Younger
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	58.55 (69.70), 6.34 – 322.37	47.47 (36.02), 6.96 - 164.32
ACQ	20 (23.0), 1 - 47	35 (23.0), 6 - 132
TperACQ (ms)	1136 (719.32), 311.60 – 3723.90	525 (176.43), 180.60 - 957.50
PTMI	.37 (.24), 0 – 1.0	.31 (.13), .12 - .69
	Measures of selectivity	
VARALT	.040 (.050), .001 - .187	.017 (.016), .001 - .050
VARATT	.036 (.049), .001 - .187	.016 (.017), .001 - .081
	Measure of information acquisition	
PATTERN	-.019 (.505), -1.0 - 1.0	.197 (.418), -.667 - 1.0

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

The following variables showed no age effects: PTMI4, $Z(N=72) = -1.49, p = .136$, VARATT4, $Z(N=72) = -1.87, p = .061$, and VARALT8, $Z(N=72) = -1.63, p = .103$.

There was a significant interaction between complexity and age group, $F(7,64) = 28.55, p < .001$; specifically in terms of PTMI, $F(1, 70) = 181.60, p < .001$; and PATTERN, $F(1, 70) = 6.978, p = .010$. Between and within group non-parametric comparisons of age group and complexity was conducted on these variables. Significant differences between older and younger participants on PTMI8 have already been reported; in addition there was a significant difference between age groups on PATTERN4, $Z(N=72) = -2.91, p = .007$. Within groups, there were significant differences of complexity in PTMI, $Z(N=72)$

= -5.18, p = .000 for the young group, and $Z(N{=}72)$ = -2.87, p = .004 for the older group. There was a significant difference within the older group on PATTERN, $Z(N{=}72)$ = -2.13, p = .033. There were no significant differences between age groups on PTMI4, $Z(N{=}72)$ = -1.49, p = .136; or PATTERN8, $Z(N{=}72)$) = -.142, p = .887, and no significant difference within the young group on PATTERN, $Z(N{=}72)$ = -1.25, p = .210.

Table 4.5 Mean dependent measures by age group for the 8x8 decision condition

	Older	Younger
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	102.12 (79.11), 1.32 – 396.31	69.72 (47.27), 15.33 - 234.71
ACQ	38 (26.63), 2 - 109	67 (49.9), 15 – 220
TperACQ (ms)	1213 (779.22), 281.10 – 3714.90	477 (142.04), 156.90 - 896.70
PTMI	.28 (.25), 0 – 1.0	.18 (.09), 0 - .38
	Measures of selectivity	
VARALT	.025 (.022), .001 - .110	.017 (.014), .001 - .063
VARATT	.027 (.036), .001 - .120	.016 (.046), .001 - .281
	Measure of information acquisition	
PATTERN	-.028 (.537), -1.0 - 1.0	.298 (.388), -.571 - 1.0

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

The interaction effects between age and complexity on PTMI and PATTERN indicate that, in terms of increasing complexity, older and younger adults responded differently on PTMI and PATTERN. When decision complexity was low, there was no significant difference between age groups in the amount of time spent on the most important attribute (PTMI). When decision complexity increased, both younger and older participants spent less time in this attribute, although younger adults spent significantly less time than older adults. In terms of PATTERN, when decision complexity was low, older adults were significantly more attribute-based than younger adults.

4.3 Discussion

This study set out to examine the effects of increasing the mismatch between task demands (operationalised by increasing complexity) and task resources (diminished resources operationalised by recruiting older adult participants) on the information acquisition process. It also aimed to explore decision making in an older adult population, through comparison with younger adults.

It was found that increasing task demand from a low complexity (4x4) to a high complexity (8x8) condition in a decision making population with diminished cognitive resources resulted in cognitive streamlining in the information acquisition process, specifically in terms of the amount of information acquired (in both absolute and relative terms), and pattern of search. In absolute terms, older adult participants spent more time making their decision, and made more acquisitions in that time, on the high complexity condition.

However, when proportionality was considered, the average, total time spent making the complex decision was proportionately significantly less than in the low complexity condition. Similarly, the proportional number of information acquisitions made in the high complexity condition was significantly less than in the low complexity condition. In addition, the number of acquisitions in the 8x8 condition averaged across the decision space indicated that at best only half the decision space was being searched, while equivalent measures for the 4x4 condition indicated that all the decision space was being search. Overall, older adults processed relatively less available information in the high complexity condition compared to the low complexity condition, indicating cognitive streamlining in terms of the amount of information processed under increased complexity.

While increasing complexity did not lead to increased selectivity of search, the pattern of search became significantly more attribute-led in the high complexity condition. Attribute-led search patterns are strongly indicative of non-compensatory decision strategies (Payne *et al.*, 1993). Non-compensatory strategy selection is an indication of increased cognitive streamlining (Payne *et al.*, 1993). This is further indication of cognitive streamlining under increased complexity. Thus, this study provides strong evidence that cognitive streamlining was adopted by older adults under conditions of increasing complexity, in terms of decreased amounts of processing and a more non-compensatory, attribute-led search style.

When the older, diminished resources population was compared to the younger population from Study 1, Chapter 2, clear differences were visible. On both complexity conditions, older adults generally took more time to acquire information, spent more time on the most important attributes, and were more selective in their searches, across both attributes and alternatives. In addition, older adults were more attribute-driven in their search than younger adults in the low complexity condition.

It is interesting to note that while the amount of information processed by the older participants decreased relatively on the high complexity condition, the amount of time spent on each acquisition did not. Regardless of complexity, older adults spent a considerable amount of time on each acquisition made, on average over a second. Thus, while they processed less information than the younger adults, older adults took longer to do so.

It is also interesting to note that, in the face of increased complexity, older adults responded differently to younger adults in terms of the proportion of time spent on the most important attribute, and in terms of the pattern of the search. While both groups spent more time on the subjectively most important attribute as complexity increased, older adults spent significantly longer on this attribute than did younger adults. This indicates that older adults were engaging in more extreme cognitive streamlining. In terms of the pattern of search, older adults were more attribute-led on the low complexity condition than the younger adults, in addition to low versus high complexity differences in older adults. This indicates that older adults were more cognitively taxed on the low complexity condition, which supports the prediction that cognitive streamlining is occurring at an earlier point in a population with diminished resources.

Generally, this study first provides additional support that decision complexity affects the information acquisition process underlying decision making, particularly in terms of the amount of information processed. Second, the results indicate that there were age effects on the information acquisition process across complexity conditions; older adults processed less information over an equivalent time period compared to younger adults, were more selective in term of their subjectively most important attribute and across attributes in general, but spent longer on each acquisition than younger adults did. Third, the interaction effects reported above for the amount of time spent in the subjectively most important attribute and the pattern of the search imply that older adults were more cognitively efficient as complexity increased: they maintained a greater amount of time spent processing their most important attribute, and engaged in more attribute-led processing under low complexity. However, older adults were also exhibiting greater cognitive streamlining in the low complexity condition than the younger adults. Thus, there is evidence that widening the mismatch between task demands and task resources by both increasing the demand and decreasing the resources does lead to increased cognitive economy in the information acquisition process.

These results are consistent with the predictions of the E-Af (Payne *et al.*, 1993): as the task demands increasingly outweighed task resources, greater cognitive economy was adopted. Across age groups, this was evident in a decrease in the amount of information processed (in both absolute and relative terms). In addition, they are consistent with the proposed hierarchy of adaptivity: that the degree of cognitive economy adopted will depend precisely on the balance between task demands and task resources. Cognitive streamlining occurs in stages of severity which relate first to a decrease in the amount of information processed, and subsequently into changes in selectivity and pattern of search. This study supports this, in that a population with diminished resources responded with greater cognitive economy than a cognitively-optimal population, in the face of equivalent task demands.

The results also provide the first evidence for older adult decision making based on a stringent process tracing protocol examining information acquisition. This evidence is consistent with the suggestions of past research with older adults and decision making based on a range of methodologies. This study supports the findings that older adults recheck decision space information less than younger adults, and use the decision space more efficiently (Charness, 1981b; Johnson, 1990; Johnson & Drungle, 2000); this is evident even in the low complexity decision condition. In addition, there is support for previous findings that older adults are more selective with regard to information processing than younger adults (Park & Shifren, 1999; Riggle & Johnson, 1996; Walsh & Hershey, 1993; Zwahr *et al.*, 1995), and that they take longer to acquire information than younger adults (Johnson, 1990; Johnson *et al.,* 1989; Riggle & Johnson, 1996). In addition, this study supports the suggestion that older adults engage in more non-compensatory decision strategies, as attribute-led processing is a key feature of non-compensatory strategies (Johnson, 1990; Payne *et al.*, 1993).

At this point, it is critical to discuss a potentially confounding conceptual issue: the relationship between ageing and expertise. Did this study really measure age-related changes, or the effects of expertise on decision making? Expertise is considered to be an exceptional competence relying on internal knowledge structures (Hakkarainen, 2002), and it is thought to reduce task demand by minimizing demands on working memory (Yekovich, Walker, Ogle, & Thompson, 1990). It is generally assumed that the domain-specific knowledge associated with expertise is impervious to age effects (see reviews by Ericsson & Lehmann, 1996; Masunaga & Horn, 2001). Some researchers argue that older adults are 'experts in life,' as they have had more practice with day to day tasks (Poon & Siegler, 1991; Takagi, 1997; Viggiano *et al.*, 2005). They argue that it is this expertise that leads to an absence of age-related decline in daily functioning, despite reported age-related declines in cognition. Previous research has demonstrated age-related changes in information processing as a result of expertise, rather than cognitive decline itself (Salthouse, 1984). Specifically, the benefits of expertise for older adults on domain-relevant tasks are often explained by reduced task demands on working memory, which could take the form of cognitive streamlining. Thus, it is possible that the results presented here are more indicative of age-related expertise in decision making, rather than an adaptive response to an increasing mismatch between task demands and resources

(Yekovich *et al.*, 1990). As such, it must be considered if the changes in information processing evident in this study are truly representative of age-related declines in cognitive resources, or are significantly influenced by age-related experience. Age versus expertise effects will be discussed further through the course of this thesis.

It can be argued that this task is relatively free of the potential confounding variable of domain-specific experience. The topic of the decision task (selecting an hotel) was specially chosen as one that all participants are likely to have experienced, and that is not affected by age (i.e. selecting a new car to purchase was eliminated as a task as it is unlikely many students will have done so). All participants reported having experience in selecting hotels. It was expected that some experience with selecting hotels may lead to a clarification of subjective preferences in hotel features, rather than developed knowledge structures about hotel decision making. In real life, it can be argued that the benefit of experience in deciding between hotels is decoding the euphemistic language of the hotel descriptions. Arguably, experience with selecting and staying in hotels is not synonymous with detailed knowledge structures gained through extensive training. However, even if experience in selecting hotels did lead to expertise in this area, it is argued that it would not account for the age effects seen in these studies. First, professional or skill expertise aside, research has demonstrated that even extensive training on a task does not mediate age effects (Meinz & Salthouse, 1998; Morrow, Menard, Stine-Morrow, Teller, & Bryant, 2001). As such, it is unlikely that a decision preference structure (i.e. hotel attribute preferences in this case) will influence performance. Second, some researchers have demonstrated that expertise cannot mitigate against age-related cognitive decline (Salthouse, 1994; Taylor, O'Hara, Mumenthaler, Rosen, & Yesavage, 2005), while others have demonstrated that it can (Salthouse, 1984). The fact that research on age and expertise has shown mixed results led to the conclusion that task-domain relevance is a crucial factor for the age-moderating effects of expertise (Morrow *et al.*, 1994; Salthouse, 2002). Older adults have been seen to be more skilled decision makers only in areas where they have greater domain specific expertise, and only on very specific tasks that reflect this expertise. It is unlikely that a significant number of participants had engaged in hotel rating as a profession; however, even if they had, it is unlikely that it would have been based on a task format of this nature, which is critical for the execution of expertise (Vicente, 1992; Vicente & Wang, 1998). It has also been demonstrated that even domain-specific expertise must be maintained with regular practice; otherwise it will not mitigate age-related cognitive declines (Ericsson, 2000). As the vast majority of the older adults in this study are retired, even if they were professional hotel raters, they would not be maintaining this professional expertise. Finally, research that aimed to separate the effects of age and expertise has demonstrated that age and expertise are not synonymous, and need to be considered separately (Patrick, 1996).

The definition of expertise includes the development of knowledge structures gained through experience. Is it possible that life experience leads to more expert, generalised knowledge, that is often termed 'wisdom'? This generalised knowledge or wisdom could result in the decision strategies that older adults regularly employ being executed more efficiently due to practice (Betsch *et al.,* 1998). While, as mentioned in the introduction, the habitual use of certain strategies can lead to maladaptive decision making, it is also possible that these well-rehearsed decision strategies happened to suit this task and thus were employed to good effect. It is argued that, while possibly more influential than domain-specific expertise, generalised knowledge is unlikely to have produced the results reported here. Whilst knowledge was previously thought to be indicative of crystallised intelligence that continues to grow throughout the lifespan, it has been demonstrated (see Salthouse, 2002) that this is not the case. While knowledge does increase from the ages of 18 to 40 years, the dominant trend in the later adult years is one of either stability of decline. Thus, while there is certainly a difference in knowledge, or generalised age-related experience, with age, it may not be as influential in the execution of cognitive tasks as previously thought. In addition, domain generalised knowledge could be either helpful (more efficient strategies due to practice) or harmful (maladaptive application of these strategies) across participants, it is unlikely that such a statistically strong shift to cognitive economy would have resulted on this task.

Thus, it is more likely that this study revealed a true, adaptive response in terms of information processing on a novel task in a fluid environment, largely independent of either domain-specific or domain generalised knowledge structures. Consequently, it is suggested that the evident age differences were not a result of age-related experience, but rather of an age-related decline in cognitive resources. However, the effects of expertise, in the domain-specific sense, will be further explored in Chapters 8 and 9 of this thesis. The effects of decision complexity and decision difficulty on experts' information acquisition in their area of expertise will be compared to the results of this study, to examine how similar or different age effects are to expertise effects (see Chapter 10). This will provide further clarity on the causes of the cognitive streamlining exhibited by the older adults in this study; if the cognitive streamlining response seen is not significantly different from that of experts, it may be judged that the shift to cognitive economy was due in part to experience, or habit. However, if the cognitive streamlining exhibited by the older adults differs from that of an expert group, it will lend support to suggestion that the shift to cognitive economy reported in this study is a truly adaptive response which is representative of a hierarchy of adaptivity.

In summary, the results of this study provide support for the predictions of the E-Af (Payne *et al.*, 1993), in that cognitive economy was the result of increased task demand. The nature of the cognitive economy adopted by this group provides insight into the process of decision making in older age. This study also provides evidence for a sensitive hierarchy of adaptivity, when compared against the previous studies reported in this thesis. A group of decision makers with diminished resources responded with greater cognitive economy than a cognitively-optimal population in the face of equivalent task demand.

Before the relationship between expertise and age is examined in more detail, the hierarchy of adaptivity will be further explored by increasing the mismatch between task demand and task resources; however, in the next study a different cause of increased task demand will be used. The study reported in the next chapter aimed to examine the effects of increasing task demand through decision difficulty (operationalised by time pressure), on the same population with diminished cognitive resources used in this study.

Chapter 5.

Study 4: The influence of increased decision difficulty and reduced cognitive resources on the information acquisition process underlying decision making

5.0 Introduction

The previous chapters in this thesis have explored the adaptive nature of decision making by varying the balance between task demand and the cognitive resources available for the task. The first two studies explored increasing task demand via increased decision complexity and decision difficulty, respectively, in a cognitively-optimal population. These studies revealed a trend towards cognitive economy as task demand increased, as predicted by the Effort-Accuracy framework (E-Af: Payne, Bettman, & Johnson, 1993).

However, this cognitive streamlining in a cognitively optimal population was only evident through a decrease in the actual amount of information processed (and in addition, acceleration of processing under greater decision difficulty), and did not translate into increased selectivity or attribute-led pattern of search. The third study, reported in Chapter 4, increased the mismatch between demand and computational availability by increasing decision complexity in a population with diminished cognitive resources. This study demonstrated that increasing the imbalance between demand and resources resulted in more severe cognitive streamlining, in the form of a relative decrease in processing and more attribute-led information acquisition. This is consistent with the proposal of a hierarchy of adaptivity, which commences with decreased processing and subsequently leads to increased selectivity and attribute-led searching as the discrepancy between task demand and resources becomes greater.

The study reported in this chapter continues to explore the effect of this imbalance on the information acquisition process underlying decision making. It explores the effects of increasing task demand by increased decision difficulty (operationalised by time pressure) in a cognitively-diminished population. In other words, this study was a replication of Study 2, Chapter 3, in an older adult population. This study had several specific objectives: first, to explore the effects of increasing task demand through decision difficulty in the context of a hierarchy of adaptivity. Second, it aimed to examine if these effects provide support for any of the theories of the effects of time pressure outlined in Study 2: acceleration (Ben Zur & Breznitz, 1981), filtration (Miller, 1960), and a shift in decision strategies (Payne *et al.*, 1993).

Third, it aimed to examine if these effects differed from those resulting from increases in decision complexity, as seen in Studies 1 and 3, Chapters 2 and 4 respectively. In a cognitively-optimal population, Studies 1 and 2 illustrated a difference in the adaptive response to demand source; in other words, participants responded differently in the face of either decision difficulty (operationalised by time pressure) or complexity (operationalised by a larger decision space). At face value, participants responded with more severe cognitive streamlining in the face of decision complexity. The previous study, Study 3, revealed that a cognitively diminished population demonstrated moderate to high levels of cognitive streamlining in the face of increased decision complexity. Thus, if decision complexity is more computationally demanding than decision difficulty, it may be conjectured that time pressure will lead to cognitive streamlining in a cognitively-diminished population, but to a lesser extent than viewed in Study 3, Chapter 4. Study 3 demonstrated a decrease in the amount of information processed and a shift to more attribute-led search patterns in response to increased complexity. A lesser, but still cognitively-economical response pattern in response to time pressure would result either in a decrease in the amount of information processed, an increase in selectivity, or both. This would provide further support for the nature of adaptivity.

In terms of time pressure, it is also possible that increasing the mismatch between cognitive resources and task demand will lead to the adoption of a different time pressure strategy than that seen in the cognitively-optimal population (acceleration, Ben-Zur & Breznitz, 1981). This could be either through filtration (Miller, 1960), or a shift in decision strategies (Payne *et al.*, 1993). These strategies may be considered more severe than acceleration, as they exclude a certain amount of information available in the decision space. If this study does provide support for a different response to time pressure than acceleration, it could explain why different theories of time pressure have been proposed in past research. For example, in some studies, filtration may occur as the mismatch between task demand and task resources in that particular study outweigh that of another study reporting acceleration. In this case, as argued in Study 2, Chapter 3, the variety of reported responses to time pressure only serve to provide support for a hierarchy of adaptivity, with the different responses representing different points along the balance of task demand and resources.

Conversely, it is also possible that the response of a cognitively-diminished population to time pressure will be cognitive overload. As this population was not cognitively overloaded by increased complexity, this would provide further evidence for the difference in the effects of demand source on the decision process.

5.1 Method

5.1.1 Participants: The same 36 older adult volunteers (22 females, 14 males, age *M* 71.5 years, *SD* 6.9, range 58-85) who participated in Study 3, Chapter 4 participated in this study.

5.1.2 Stimuli/Procedure: The procedure followed was identical to that of Study 2, except that older adults were given the option between a regular mouse and an ergonomic, anti-arthritis mouse. As in Study 2, participants were asked to rate their subjective experience of time pressure on a scale of 0 – 3 (0 = no time pressure, 1 = felt under a lot of time pressure, 2 = felt under moderate time pressure, 3 = felt under no time pressure),

5.1.3 Dependent measures: In this study, the seven previously published measures that were used in previous studies were used: relating to amount of processing (TdTIME, ACQ, TperACQ, PTMI), selectivity (VARALT, VARATT), and pattern of search (PATTERN).

5.1.4 Analysis: The data analysis procedure followed that outlined in Study 2, Chapter 3. In addition, a repeated measures MANOVA of difficulty and age group was conducted on the transformed variables. A series of t-tests, between and within age groups, were conducted to explore any interactions.

5.2 Results

All data were log transformed due to positive skew. There were no issues of co-linearity of variables, so all were included in subsequent analysis (see Table 5.2). Tables 5.1, 5.3 – 5.6 contain raw score descriptives, for ease of interpretation. A manipulation check for time pressure revealed that the median rating for this participant group was 2 (range 1-3), indicating that the older adult group felt moderate time pressure in the time pressure condition.

5.2.1 4x4 condition

As reported in Study 3, Chapter 4.

Table 5.1 Mean dependent measures by decision condition

	4x4	4x4 time pressure
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	58.55 (69.70), 6.34 – 322.37	28.79 (27.97), .519 - 123.20
ACQ	20 (23.02), 1 - 47	11 (7.4), 1 – 25
TperACQ (ms)	1136 (719.32), 311.60 – 3723.90	1022 (896.88), .889 – 4155.10
PTMI	.37 (.24), 0 – 1.0	.43 (.30), 0 – 1.0
	Measures of selectivity	
VARALT	.040 (.050), .001 - .187	.055 (.057), .002 - .187
VARATT	.036 (.049), .001 - .120	.060 (.072), .001 - .187
	Measure of information acquisition	

PATTERN	-.019 (.505), -1.0 - 1.0	-.069 (.673), -1.0 - 1.0
% acquisition time	39	39

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative-led (+) processing.

5.2.2. 4x4 time pressure condition

In the time pressure condition, if all items in the decision space were considered, the average duration and number of acquisitions per item would be 1.8s and .7 respectively. This implies that less than a third of the items in the decision space were considered. Factored out by alternative, this would average at 7.2s and 2.7 acquisitions per alternative. The average time per acquisition was quite high, at approximately one second for each acquisition. Participants spent on average 43% of the time on their subjectively most important attribute, which was significantly more than the 25% of time they should have spent if processing were equivalent across the four attributes, $t(35) = 3.64, p = .001$. Thus, in terms of information processing, the demand on this task appeared to be moderate/high, with not all of the available information in the decision space searched, each acquisition took approximately a second, and there was evidence of selectivity of processing in terms of high PTMI.

In terms of the selectivity of the search pattern, it appeared to be selective across both attributes and alternatives. Both VARATT and VARALT are very high, compared to previous standards (Payne, Bettman, & Johnson, 1988) as well as compared to the younger group under time pressure, VARATT, $t(70) = -3.78, p = .001$, VARALT, $t(70) = -2.79, p = .007$.

The information acquisition pattern was neither significantly attribute nor alternative-led, $t(35) = -.613, p = .544$.

Table 5.2 Correlation matrix for dependent variables: 4x4 above the diagonal, 4x4 time pressure below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.68‡	.35†	-.16	-.28	-.31	.24
ACQ	.53‡		-.18	-.27	-.54 ‡	-.54 ‡	.35†
TperACQ	.28	-.26		.21	.30	.20	.15
PTMI	-.20	-.31	.10		.78 ‡	.32	-.24
VARATT	-.54‡	-.72‡	.01	.46‡		.57‡	-.21
VARALT	-.32	-.63‡	.27	.18	.42†		-.28
PATTERN	.23	.24	.23	-.08	-.37†	.14	

Note. † = p <.05 level (2 tailed); ‡ = p < .01 level (2 tailed)

5.2.3 A comparison of the 4x4 and 4x4 time pressure conditions

In terms of the patterns of correlation between conditions (see Table 5.2), there are a several consistencies between, and across, conditions. As with complexity, TdTIME was positively correlated with the number of acquisitions made. ACQ was also negatively correlated with VARATT and VARALT, indicating that more selective searches involved fewer attributes.

However, there are also a number of inconsistencies in the pattern of correlations, both within the difficulty conditions, and also compared to the complexity conditions. TperACQ, which has not previously been correlated with any other variable, was positively correlated with TdTIME in the low difficulty condition, indicating that for the older adults, a longer decision time was due to more time spent in each attribute (whereas for the younger adults, under difficulty, longer TdTIME was positively correlated with more acquisitions). Additionally, in the low difficulty condition, ACQ and PATTERN were positively correlated, indicating that more compensatory searches were associated with more acquisitions being made. In the high difficulty condition, PATTERN is negatively correlated with VARATT, which is logical and indicative of a consistently economical search under time pressure.

A repeated measures MANOVA of difficulty (4x4, 4x4 time pressure) for the transformed variables (TdTIME, ACQ, TperACQ, PTMI, VARALT, VARATT, and PATTERN) revealed a main effect of difficulty, $F(7,28) = 5.70, p < .001$. This arose through significant effects of difficulty in TdTIME, $F(1, 35) = 25.76, p < .001$, ACQ, $F(1, 35) = 26.45, p < .001$, and VARATT, $F(1, 35) = 6.86, p = .013$. There was a significant trend towards difficulty for PTMI, $F(1, 35) = 3.87, p = .057$. No significant effects for difficulty were found for TperACQ, $F(1, 35) = 2.84, p = .101$, VARALT, $F(1, 35) = 2.45, p = .127$, and PATTERN, $F(1, 35) = .222, p = .641$. There was significant deviation from normality for the residuals of 6 variables in the time pressure condition (TdTIME, ACQ, TperACQ, PTMI, VARATT, PATTERN) and 1 variable in the baseline condition (ACQ). Non-parametric comparisons of difficulty level were conducted. As in the MANOVA, there were consistently significant effects of difficulty on TdTIME, $Z(N=36) = -4.16, p < .001$, ACQ, $Z(N=36) = -4.08, p < .001$, PTMI, $Z(N=36) = -2.08, p = .038$, and VARATT, $Z(N=36) = -2.49, p = .013$. In addition, there was a significant effect of difficulty on TperACQ, $Z(N=36) = -2.19, p = .028$. There were consistently no effects of difficulty on VARALT, $Z(N=36) = -1.50, p = .133$, and PATTERN, $Z(N=36) = -.37, p = .711$. Thus, under time pressure, participants took significantly less time to make their decisions, made significantly fewer acquisitions, spent more time acquiring information on their subjectively most important attributes, and were more selective in acquiring information across attributes.

The ratio of acquisition time to deliberation time was not significantly different across conditions, $t(35) = .78, p = .460$, suggesting the level of processing for the information that was acquired was consistent between conditions.

5.2.4 A comparison of the difficulty (4x4 time pressure) and complexity (8x8) conditions in an older adult population

To account for decision size differences, variables relating to the amount of processing which are susceptible to decision size (TdTIME, ACQ, PTMI) for both difficulty (4x4 time pressure) and complexity (8x8) conditions were transformed into ratio values in terms of their baseline 4x4 values, i.e. TdTIME 8x8/TdTIME 4x4 and TdTIME 4x4 time pressure/TdTIME 4x4 (see Table 5.3). A series of paired t-tests for

Table 5.3 Transformed ratio values for amount of processing measures in an older adult population

	4x4 time pressure	8x8
	Ratio measures of information processing	
	M (*SD*)	*M* (*SD*)
rTdTime (s)	.65 (.49)	2.55 (2.20)
rACQ	.68 (.41)	2.08 (1.17)
rPTMI	1.18 (.67)	.77 (.44)

Note. rTdTime = total time to decision ratio; rACQ= ratio of number of information boxes examined; rTperACQ = time per information acquisition ratio; rPTMI = ratio of proportion of time spent on subjectively most important attribute

these transformed values for the older adult group revealed significant differences in demand source (complexity vs. difficulty) for TdTIME, $t(35) = -5.07, p < .001$, ACQ, $t(35) = -7.87, p < .001$, and PTMI, $t(35) = 3.11, p = .004$. Thus, complexity as the demand source, led to a significantly longer average total decision time, and a significantly greater number of acquisitions. In addition, complexity resulted in significantly less time spent on the subjectively most important attribute, compared to difficulty.

A repeated measures MANOVA of decision type (4x4 difficulty, 8x8 complexity) for the transformed dependent variables revealed a main effect of decision type, $F(4,32) = 3.87$, $p = .011$. Specifically, of the variables that are not susceptible to decision size effects (TperACQ, VARALT, VARATT, PATTERN), there were significant effects of decision type for, VARATT, $F(1,35) = 9.09$ $p = .005$, and VARALT, $F(1,35) = 5.63, p = .023$. There were no significant effects of decision type for TperACQ, $F(1,35) = 3.65, p = .064$, or PATTERN, $F(1,35) = 0.14, p = .708$. Participants did not differ in the amount of time per acquisition, or type of search pattern in the face of different computational demand sources. However, they were more selective across attributes and alternatives under increased task difficulty, than they were under increased task demand.

Table 5.4 Mean dependent measures by decision condition, older adults

	8x8	4x4 time pressure
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	102.12 (79.11), 1.32 – 396.31	28.79 (27.97), .519 - 123.20
ACQ	38 (26.63), 2 - 109	11 (7.4), 1 – 25
TperACQ (ms)	1213 (779.22), 281.10 – 3714.90	1022 (896.88), .889 – 4155.10
PTMI	.28 (.25), 0 – 1.0	.43 (.30), 0 – 1.0
	Measures of selectivity	
VARALT	.025 (.022), .001 - .110	.055 (.057), .002 - .187
VARATT	.027 (.036), .001 - .120	.060 (.072), .001 - .187
	Measure of information acquisition	
PATTERN	-.028 (.537), -1.0 - 1.0	-.069 (.673), -1.0 - 1.0
% acquisition time	45	39

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

5.2.5 A comparison of the 4x4 and 4x4 time pressure conditions across age groups

A repeated measure MANOVA of difficulty (4x4, 4x4 time pressure) and age group (young, older) for the transformed dependent variables (TdTIME, ACQ, TperACQ, PTMI, VARALT, VARATT, PATTERN) revealed a main effect of difficulty $F(7, 64) = 8.51, p < .001$.

Table 5.5 Mean dependent measures by age, 4x4 condition

	Older	Young
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	58.55 (69.70), 6.34 – 322.37	47.47 (36.02), 6.96 - 164.32
ACQ	20 (23.02), 1 - 47	35 (23.02), 6 – 132
TperACQ (ms)	1136 (719.32), 311.60 – 3723.90	524 (176.43), 180.60 –957.50
PTMI	.37 (.24), 0 – 1.0	.31 (.13), .12 – .69
	Measures of selectivity	
VARALT	.040 (.050), .001 - .187	.017 (.016), .001 - .050
VARATT	.036 (.049), .001 - .120	.016 (.017), .001 - .081
	Measure of information acquisition	
PATTERN	-.019 (.505), -1.0 - 1.0	.197 (.418), -.667 - 1.0
% acquisition time	39	39

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME x 100).

This arose through effects in TdTIME, $F(1, 70) = 46.53, p < .001$, ACQ, $F(1, 70) = 41.15, p < .001$, and TperACQ, $F(1, 70) = 7.03, p = .010$. Regardless of age, increased difficulty reduced the average, total decision time, number of acquisitions, and time spent on each acquisition. There were no significant effects of difficulty on PTMI, $F(1, 70) = .66, p = .420$, VARATT, $F(1, 70) = .66, p = .421$, VARALT, $F(1, 70) = 2.38, p = .128$, or PATTERN, $F(1, 70) = .32, p = .575$.

There were also main effects of age group, for ACQ, $F(1, 70) = 21.48, p < .001$, TperACQ, $F(1, 70) = 18.63, p < .001$, PTMI, $F(1, 70) = 10.53, p = .002$, VARATT, $F(1, 70) = .9.22, p = .003$, and VARALT, $F(1, 70) = 4.68, p = .034$. There was no main effect of age group on TdTIME, $F(1, 70) = .26, p = .613$. There was significant deviation from normality for the residuals of 6 variables in the time pressure condition (TdTIME4, ACQ, TperACQ, VARALT, PATTERN) and 1 variable in the no time pressure condition (ACQ). Non-parametric comparisons of age were conducted on the main effects of age between decision conditions, to explore age group differences more conservatively.

Table 5.6 Mean dependent measures by age, 4x4 time pressure condition

	Older	Young
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	28.79 (24.97), .519 – 123.30	28.18 (29.91), 3.13- 177.18
ACQ	11 (7.44), 1 - 25	25 (16.08), 5 – 68
TperACQ (ms)	1022 (896.88), .889 – 4155.10	417 (168.12), 167.80 –843.60
PTMI	.43 (.30), 0 – 1.0	.29 (.16), .09 – 1.0
	Measures of selectivity	
VARALT	.055 (.057), .002 - .187	.019 (.032), .001 - .187
VARATT	.060 (.072), .001 - .187	.027 (.035), .001 - .187
	Measure of information acquisition	
PATTERN	-.069 (.673), -1.0 - 1.0	.175 (.477), -1.0 - 1.0
% acquisition time	39	37

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME x 100).

There were significant effects for age group in variables in the no time pressure conditions, ACQ, $Z(N=72) = -3.04, p = .002$, TperACQ, $Z(N=72) = -4.98, p < .001$, and VARALT, $Z(N=72) = -2.48, p = .013$. The following variables in the no time pressure condition showed no age effects: TdTIME, $Z(N=72) = -.15, p = .884$, and PATTERN, $Z(N=72) = -.70, p = .704$, PTMI, $Z(N=72) = -1.49, p = .136$, and VARATT, $Z(N=72) = -1.87, p = .061$. In terms of the time pressure condition, there were significant age effects for ACQ, $Z(N=72)) = -4.24, p < .001$, TperACQ, $Z(N=72) = -4.30, p < .001$; PTMI, $Z(N=72) = -2.03, p = .042$, VARATT, $Z(N=72) = -3.20, p = .001$; and VARALT, $Z(N=72) = -2.69, p = .007$. There were no age effects in the time pressure condition for

TdTIME, $Z(N=72)) = -.20$, $p = .839$. There was a trend towards significance for PATTERN, $Z(N=72) = -1.89$, $p = .059$.

There was no overall interaction effect between decision difficulty and age group, $F(7,64) = 1.15$, $p = .345$. However, as the MANOVA is a very conservative tool, at the risk of making a Type 2 error, it was decided that any significant interactions between variables in the absence of an overall interaction effect would be explored in this thesis. The rationale for this decision will be explored in Chapter 10. When interactions were examined across dependent variables, there were significant decision difficulty (time pressure/no time pressure) and age group (young/old) interactions on PTMI, $F(1, 70) = 4.01$, $p = .049$, and VARATT, $F(1, 70) = 5.32$, $p = .024$. A series of between and within group comparisons of age and difficulty were conducted on these variables, to explore them further. There was no significant difference between age groups on PTMI in the no time pressure condition, $t(70) = -1.30$, $p = .198$. However, there was a significant difference between the age groups on PTMI in the time pressure condition, $t(70) = -2.48$, $p = .016$, with older adults spending more time on their subjectively most important attribute than younger adults.

In terms of VARATT, between age groups, there was a significant difference on VARATT in the no time pressure condition, $t(70) = -2.23$, $p = .031$; and in the time pressure condition, VARATT, $t(70) = -3.18$, $p = .003$. Older adults were more selective than younger adults in the time spent on different attributes in the time pressure condition; they were also more selective than younger adults in the no time pressure condition. While time pressure did not affect selectivity in younger adults, it caused older adults to become significantly more selective.

5.3 Discussion

This study set out to examine decision adaptivity, by exploring the effects of increasing the mismatch between task demand (operationalised by decision difficulty) and task resources (diminished resources operationalised by recruiting older adult participants) on the information acquisition process. It also aimed to obtain some insight into how older adults make decisions under conditions of difficulty, compared to younger adults. In addition, it set out further to compare the effects of increased decision difficulty on the information acquisition process underlying decision making with those caused by increased decision complexity.

It was found that increasing task demand from a low difficulty (no time pressure) to a high difficulty (time pressure) level in a decision making population with diminished cognitive resources led to cognitive streamlining in terms of the amount of information processed and selectivity of processing. Specifically, as decision difficulty increased, participants took significantly less time to make their decisions, made significantly fewer acquisitions, spent more time acquiring information on their subjectively most important attributes, and were more selective in acquiring information across attributes. Thus, as decision difficulty increased, older adults processed less information for less time, and adopted a more selective search pattern. This is consistent with evidence for shifts to more non-compensatory decision strategies, as predicted by the E-Af (Payne *et al.,* 1993).

This study aimed to gain further insight into older adult decision making, by comparing the results of this study with those of Study 2, Chapter 3 (young adults under time pressure). It was mentioned in Chapter 4, Study 3, that older adults already appeared to experience cognitive strain on the baseline, low complexity condition. As detailed above, this cognitive strain was exacerbated by an increase in decision difficulty. On average, older adults made fewer acquisitions, spent more time on each acquisition, and were more selective across alternatives than younger adults. As difficulty increased, it can be argued that there were interactions that cannot be overlooked between age and difficulty on the proportion of time spent in the subjectively most important attribute and the selectivity of search across attributes. Older adults spent more time on their subjectively most important attribute as decision difficulty increased, while young adults did the opposite. In addition, older adults were more selective across attributes as time pressure increased, compared to younger adults. As there is evidence for the use of more stringent, non-compensatory strategies for the older adult group, this implies that older adults were more cognitively-economical than younger adults under time pressure. These results are inconsistent with the phenomenon of cognitive overload; rather they are consistent with a positive outcome in terms of the adoption of more streamlined decision strategies, as predicted by the E-Af (Payne *et al.*, 1993).

In terms of support for the theories of time pressure, the results of this study are not consistent with the nature of the cognitive response in the face of increasing decision difficulty reported in Study 2, Chapter 3. Study 2 provided evidence for the theory of increased acceleration of processing in response to time pressure (Ben Zur & Breznitz, 1981), although a more global change in decision strategy could not be excluded. In this study, there was no evidence for acceleration of processing: while the average total decision time did decrease as a result of increased decision complexity, the participants did not decrease the amount of time spent on each acquisition, as in Study 2.

Rather, the older adults reduced the amount of information processed, and became more selective in their search as decision difficulty increased: they acquired less information, focused on subjectively important information, and engaged in an increasingly selective search across attributes. This arguably provides support for filtration, as the nature of the changes to information processed can be likened to a perceptual narrowing in response to stress (Keinan, 1987). However, a shift in decision strategies cannot be excluded. As mentioned earlier, there was no evidence for increased attribute-led searching as decision difficulty increased. Changes in search pattern are generally considered to be indicative of a change in decision strategies (Payne *et al.*, 1993); however, the shift to more attribute-based processing has been shown not to be a definitive marker for shifts in decision strategies, which can be generally characterised by varying changes in the amount of information processed, selectivity, and/or search patterns (Payne, Bettman, & Luce, 1996). It may be argued that the results presented above are representative of a shift in decision strategies, that include an element of filtration.

The results of Studies 2 and 4, Chapters 3 and 5, together provide support for the claim that mild/moderate time pressure can be a positive factor for decision making in terms of the E-Af, in that it encourages cognitive economy (Dhar & Nowlis, 1993, Payne *et al.,* 1993). In addition, these studies provide support for the idea that acceleration and filtration are distinct mechanisms: young adults adopted acceleration in the face of increasing decision difficulty with no evidence for filtration, older adults adopted an element of filtration with no evidence of acceleration. They also suggest that filtration may be the more extreme of the two in terms of cognitive economy, as filtration was adopted by the participant population under greater cognitive strain. However, neither study can preclude changes in decision strategies in response to increased decision difficulty, as both acceleration (likened to a decrease in processing) and filtration (likened to selectivity) may be considered to be indicative of a wider shift in decision strategies.

The results of this study also provide evidence for a differential effect on decision processing by demand source. It was suggested in Chapter 3, on the basis of the younger adult data from Studies 1 and 2, that decision complexity was the more computationally demanding of the two: decision difficulty affected the speed at which information was processed but not the overall amount processed, while increasing decision complexity reduced the actual amount of information processed. For a population with diminished cognitive resources, decision complexity also appeared (at face value) to be computationally more demanding. For an older adult population, increased complexity demanded a relatively greater amount of information processing, and an increasingly attribute-led search pattern. Decision difficulty led to a decrease in the amount of information processed and an increase in selectivity. As it is generally agreed that pattern of search is indicative of the most severe type of streamlining (Payne *et al.*, 1993), this suggests that decision complexity was more cognitively effortful than decision difficulty for the older adults.

In addition, the greater processing of the subjectively most important attribute for older adults was more significant with increased decision complexity. Overall, this indicates a relatively greater amount of processing occurred in the complex decision, compared to the difficult decision. This is consistent with the results from the younger adult group in Chapter 3, Section 3.2.4.

In summary, first, this study provides support for the theory of filtration in response to time pressure (Miller, 1960), although the possibility of shifts in decision strategies cannot be excluded. Second, it provides further evidence that widening the mismatch between task demands and task resources by both increasing the demand and decreasing the resources leads to increased cognitive economy in the information acquisition process. This is consistent with the predictions of the E-Af (Payne *et al.*, 1993). Third, this study adds robustness to the findings relating to older adult decision making in Study 3, Chapter 4, by replicating the age effects found in the previous study. In general, older adults make fewer acquisitions for an equivalent amount of time, process more information about their subjectively most important attribute, and are more selective across attributes and alternatives than younger adults. Fourth, compared to Study 2, Chapter 3, this study revealed that that older adults were more cognitively economical than younger adults as decision difficulty increased: they maintained a greater amount of time spent processing their most important attribute, and engaged in more selective processing. Finally, when considered in light of Studies 1-3, this study provides further evidence for a hierarchy of adaptivity that is contingent on the precise balance between task demand and task resources, and one that is subject to a hierarchical response in terms of cognitive expenditure in the face of increasing task demand. This will be discussed further in Chapter 10. In addition, Studies 1-4 suggest that task demand may not be a unitary, simple concept as was previously considered: measurable on a single continuum in terms of quantitative increases. It is possible that task demand may differ qualitatively depending on the source of the demand. Increases in task demand by decision complexity and decision difficulty result in different cognitive responses. This may be because the computational loads caused by complexity and difficulty were not equivalent levels of demand (and thus represent quantitative increases), but it may also may suggest that the nature of the task demand is critical for determining cognitive response.

The possible weakness in this study relates to the conceptual and methodological issues pertaining to the ecological validity of testing time pressure in a laboratory, data analysis, and the distinction between age and experience, that have been discussed in previous chapters. Chapters 8 and 9 will continue to address the latter, through exploring the effects of expertise on decision making. This will enable a direct comparison of the effects of expertise and ageing on the information acquisition process, in order either to distinguish or to reconcile the two.

Before the effects of expertise are examined, the domain generalisability of the effects of decision complexity and decision difficulty will be explored, in another cognitively-optimal population and with another decision type. This new, cognitively-optimal population also represents a novice group in the area of expertise that will be studied in Chapter 8 and 9 and, as such, provides a baseline for comparison of the effects of expertise on decision making.

Chapter 6.

Study 5: Examining the effects of decision domain and decision complexity on the information acquisition process underlying decision making

6.0 Introduction

The previous studies reported in this thesis have provided support for the predictions of the Effort-Accuracy framework proposed by Payne, Bettman, & Johnson (E-Af; 1993): increased task demand led to increased cognitive streamlining. Such results were obtained using a decision domain relating to selecting a hotel for a holiday. Task demand is determined by decision complexity and decision difficulty: up to this point, complexity has been largely defined by the size of the decision space (Hogarth, 1975; Payne, 1976, 1982). While research acknowledges that other structural features relating to the decision space also influence the level of demand (see Chapter 1, Section 1.7.3), the effect of the actual decision topic, or decision domain, on the information acquisition process has largely been ignored.

Generally, research has demonstrated that there are domain differences in terms of the decision process. Specifically, health and medical decisions have been found to show different patterns from analogous decisions in other domains, such as money (Redelmeier & Shafir, 1995; Redelmeier & Tversky, 1990, 1992). However, these patterns relate to decision outcome and preference reversals rather than the information acquisition process underlying decision making.

The studies reported in the next two chapters have three aims: first, to further explore the E-Af (Payne *et al.*, 1993) through increasing task complexity and task difficulty respectively in a cognitively optimal population. Second, to explore decision domain differences in the information acquisition process, under equivalent conditions of task demand. Specifically, the domain of medical decision making will be compared to the domain of holiday decision making studied in Chapters 2 and 3, in the face of increasing task complexity and difficulty respectively, and in an equivalent young population. If support for the E-Af can be found across different populations and in different decision domains (i.e. similar patterns of cognitive economy in the face of increased task demand), it will add credibility both to these results and to the framework itself (McCall, 1980). Conversely, if inconsistent patterns of information acquisition emerge in different domains in the face of equivalent task demands, it would suggest that decision domain is a previously overlooked and critical feature in the E-Af. Third, the next two studies aimed to begin examining the effects of enhanced resources on the hierarchy of adaptivity. They provide a baseline in the medical decision making domain in terms of minimal knowledge and optimal cognitive resources, to enable a comparison of enhanced cognitive resources operationalised by medical expertise that will take place in Studies 7 and 8, Chapters 8 and 9 respectively.

Thus, the study reported in this chapter aimed to examine the effects of increased decision complexity on the information acquisition process in the medical domain, and to examine specifically to what degree the pattern of results found in Study 1 (increased cognitive streamlining in the face of increased decision complexity) would be replicated in an alternative domain. As outlined in Study 1, increased decision complexity, which represents an increase in task demand, should lead to an increase in cognitive economy as predicted by the E-Af (Payne *et al.*, 1993). The results of Study 1 were consistent with these predictions, in that a group of cognitively-optimal participants decreased the amount of information processed in the face of increased complexity. The participant population in Study 1 were psychology undergraduates, and the decision domain was selecting a hotel for a holiday. The study reported here aimed to examine the effect of increased decision complexity on the information acquisition process in a population of medical students, on a medical decision. The population used in this study was selected as it represented another cognitively-optimal population, but one that also had some, minimal domain-specific medical knowledge to enable them to comprehend the decision task. As this population was not yet medically qualified, had not had extensive hospital experience, and less than 10 years experience in their domain, they may not be considered experts in their field (Chase & Simon, 1973; Chi, Glaser, & Farr, 1988; Ericsson & Smith, 1991; Hayes, 1985). The medical decision spaces for both the low and high complexity conditions were identical in size (4x4 for the low complexity condition, and 8x8 for the high complexity condition) and similar in the presentation of information to the holiday decisions in Study 1. As such, by traditional assumptions in the literature, computational demand between the two domains on these decision tasks may be considered equivalent.

It is may be expected that increased cognitive load due to increased decision complexity will result in cognitive streamlining, consistent with the predictions of the E-Af (Payne *et al.*, 1993). If decision domain does not influence task demand, changes in the information acquisition process as complexity increases should mirror those of Study 1. Specifically, if the decisions presented in this study are analogous to those in Study 1, it was expected that increased complexity would lead to a relative decrease in the amount of information processed.

However, it may be that, while the decision spaces used in this study are equivalent to those in Study 1, Chapter 2 in terms of size, there are decision domain effects on task demand. These domain effects could represent quantitative additions to task demand (i.e. the decision is simply harder), or qualitative effects on demand (the decision is inherently different and this difference leads to alternative patterns of information acquisition). If task demand is increased in the medical domain, either quantitatively or qualitatively, it is possible that this population may exhibit more extreme cognitive streamlining than that seen in Study 1. Conversely, it is also possible that the small amount of domain-specific knowledge held by this sample of medical students may enhance their cognitive resources, and result in less cognitive streamlining than was exhibited by the psychology students in Study 1.

6.1 Method

6.1.1. Participants: 12 University of Southampton medical students in their 4th and 5th years of a 5 year program (6 males, 6 females, age *M* 22 years, *SD* 1.5, range 18 - 26) participated in this study.

6.1.2 Stimuli: The participants for the medical domain decisions completed all decision conditions (4x4, 4x4 time pressure, and 8x8) in one data collection session. As outlined in Study 1, the decision conditions were counterbalanced across participants, 2 participants received one of the six condition orders. The stimuli of interest to this study were 4 sets of decisions relating to selecting a patient for immediate medical treatment in an accident and emergency hospital department (A&E) scenario. The decision conditions (low vs. high complexity) were represented in the form of decision matrices. Four of the decision matrices were low complexity (4 alternatives x 4 attributes) and 4 of the decision matrices were high complexity (8x8). Decision matrices of this size, with equal numbers of attributes and alternatives, were selected for the reasons outlined in Study 1, Chapter 2, Section 2.1.2. As in Studies 1 and 3, Chapters 2 and 4, this resulted in a low complexity condition with a total of 16 items of information, and a high complexity condition with a total of 64 items of information.

Each alternative in the decision matrices represented a patient profile, i.e. a range of symptoms from a hypothetical 'patient' presenting themselves to A&E. Each alternative consisted of a certain number of attributes (4 in the 4 alternative decision, and 8 in the 8 alternative decision), each of which was a symptom: pulse per minute, blood pressure in millimetres of mercury (mmHg; a measure of pressure commonly used when measuring blood pressure), pO2 (partial pressure of oxygen in the blood measured in kilopascals), a summary patient history, Glasgow Coma Scale score (GCS, ranges from 3: completely unconscious, to 15: fully awake and orientated), respiratory rate, breath sounds, and cardiovascular and chest examination (see Appendix C for descriptions of these attributes). These attributes were presented in numerical form where possible; where this was not possible verbal descriptions were kept as brief as possible in an attempt to maintain equivalence of computational load per attribute. Patient profiles were also created with the assistance of the Advanced Trauma and Life Support (ATLS: American College of Surgeons, 1997) handbook, which is used to train doctors in A&E situations. An A& E consultant of 20 years medical experience assisted in the creation of the patient profiles in what constituted the decision matrices, to ensure that the patients' symptoms were realistic and representative of actual decisions made in A&E. In addition, it was critical that the level of demand of the task alternatives was judged to be equivalent to those presented in the holiday decision matrices of Studies 1-4, to enable comparison of the information acquisition process in same-size decision spaces. All of the attributes were used in the 8x8 decisions, those deemed the most basic and important by the consultant were used in the 4x4 decision (pulse, blood pressure, pO2, and the summary patient history). The symptoms that were represented verbally were represented as simply as possible, as advised by the A&E consultant such that they did not lose their medical validity.

The order of the attributes in each matrix was counterbalanced using a Latin Square design (for the 8x8 condition, this was done separately for the first four attributes and then the second four attributes), resulting in 4 unique 4x4 and 4 unique 8x8 matrices across participants. In addition, the order of presentation of the 4x4 and 8x8 matrices was counterbalanced across participants. All decision matrices were presented, and data recorded, within Mouselab on an IBM Pentium 4 PC with a Windows XP environment and screen resolution of 1024 x 768 pixels and diameter of 15.5 inches.

6.1.3 Procedure: Participants followed the same procedure as that outlined in Study 1. They were asked to determine which of the 'patients' (one alternative being equivalent to one patient) should be given priority treatment in an A&E setting. They were given an unlimited amount of time in which to complete the decisions. After the decision had been made, participants were asked to rate all 8 attributes in terms of subjective importance on a scale of 1-8.

6.1.4 Dependent measures: In this study, the seven previously published measures that were used in previous studies were used: relating to amount of processing (TdTIME, ACQ, TperACQ, PTMI), selectivity (VARALT, VARATT), and pattern of search (PATTERN).

6.1.5 Analysis: The data analysis procedure followed that outlined in Study 1, Chapter 2, Section 2.1.4. Also, to compare decision domains, a repeated measures MANOVA of complexity (low vs. high) and decision domain (medical vs. holiday) was conducted on the variables. A series of non-parametric tests, between and within decision domains, was conducted to explore any interactions.

6.2 Results

With the exception of PATTERN and PTMI, data were log transformed due to positive skew. None of the variables was excluded on the grounds of co-linearity (see Table 6.2). Tables 6.1, 6.3, and 6.4 contain raw score descriptives for ease of interpretation.

6.2.1 The 4x4 condition:

In the 4x4 decision condition, if all items of information were considered, this would average out at 3.9s and 2.4 acquisitions per item. If this is factored out in terms of alternatives, this would average at 15.4s and 9.5 acquisitions per alternative. As there were 16 pieces of information available in the decision space, this implies a number of repetitions of acquisitions. Participants spent, on average, 25% of the decision time considering values related to their subjectively most important attribute (PTMI). This is exactly what would be expected if time were distributed equally across the four attributes. Thus, in terms of information processing, the demand appeared to be mild in the 4x4 condition. Participants were able to make multiple acquisitions and to take a reasonable amount of time to consider attributes and alternatives.

In terms of the selectivity of search, the results imply a search that was selective across alternatives, and reasonably consistent across attributes (Payne, Bettman, & Johnson, 1988). The pattern of the search was not strongly attribute or alternative-led, $t(11) = .954$, $p = .360$.

Table 6.1 Mean dependent measures by decision condition

	4x4	8x8
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	61.73 (43.17), 16.42 – 180.72	124.53 (89.68), 13.40 - 263.80
ACQ	38 (20.65), 13 - 87	96 (72.9), 10 – 226
TperACQ (ms)	879 (295.53), 510.40 – 1426.10	665 (218.84), 316.50 – 1080.30
PTMI	.25 (.08), .13 – .40	.33 (.25), .33 – 1.0
	Measures of selectivity	
VARALT	.031 (.016), .001 - .048	.013 (.013), .002 - .040
VARATT	.017 (.069), 0 - .240	.018 (.030), 0 - .110
	Measure of information acquisition	
PATTERN	.113 (.410) -.739 - 684	.001 (.479), -.800 - .732

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

6.2.2 The 8x8 condition:

In the 8x8 decision condition, if every item were considered, this would average at 7.9s and 6 acquisitions per item. This equates to 31.6s and 24 acquisitions per alternative. Participants spent on average 33% of the decision time considering values appertaining to their subjectively most important attribute (PTMI), which is significantly more than they would have spent if time were distributed equally across attributes (12.5% of the time in each one), $t\,(11) = -\,563.51, p < .001$. Thus, in terms of information processing, the demand appears to be moderate/high in the 8x8 condition.

In terms of the selectivity of the search, the results suggest the use of consistent search strategies for this decision, as the value was below .040. In terms of PATTERN the search was neither strongly attribute nor alternative-led, compared to a consistent search value of 0, $t(11) = .954, p = .360$.

Table 6.2 Correlation matrix for dependent variables: 4x4 above the diagonal, 8x8 below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.51	.13	-.09	-.43	-.35	.06
ACQ	.76‡		-.09	-.13	-.28	-.49	.18
TperACQ	.61†	.35		-.40	.03	-.06	.30
PTMI	-.58†	-.57	-.51		-.18	.29	.12
VARATT	-.52	-.53	-.40	.58‡		.09	-.27
VARALT	-.66†	-.64†	-.49	.11	.15		-.19
PATTERN	.80‡	.77‡	.47	-.68†	-.65†	-.43	

Note. † = p <.05 level (2 tailed); ‡ = p < .01 level (2 tailed)

6.2.3 A comparison of the 4x4 and 8x8 conditions:

Interestingly, the pattern of correlations between conditions for this group is not consistent between conditions, implying very different patterns of search contingent upon complexity (see Table 6.2). While there were no positive or negative correlations under low complexity (indicating no strongly logic, ordered search occurred), a number of variables are correlated under high complexity. TdTIME was significantly positively correlated with ACQ (as seen on all previous studies), and also with PATTERN. TdTIME was also significantly positively correlated with TperACQ, indicating that longer decision times were related to both more, and longer, acquisitions under high complexity. TdTIME was also negatively correlated with PTMI, VARATT, and VARALT, which are indicators of efficient (non-compensatory) search patterns. This is reinforced by the positive correlation between ACQ and PATTERN, and the negative correlation between ACQ and VARALT. Other correlations bear out the suggestion that more efficient searches were occurring under high complexity, including the positive correlation between PTMI and VARATT, and the negative correlations between PATTERN and PTMI and VARATT respectively.

A repeated measures MANOVA of complexity (4x4, 8x8) for the transformed dependent variables (TdTIME, ACQ, TperACQ, VARALT, VARATT) and the variables PTMI and PATTERN revealed a main effect of complexity, $F(7,4) = 11.34, p = .013$. This arose through significant effects of complexity in TdTime, $F(1, 11) = 5.33, p = .040$; in ACQ, $F(1, 11) = 18.71, p = .002$; TperACQ, $F(1, 11) = 100.56, p < .001$, and in PTMI, $F(1, 11) = 79.63, p < .001$. No significant effects for complexity were found for VARATT, $F(1, 11) = .243, p = .633$; VARALT, $F(1, 11) = .233$, $p = .640$; or PATTERN, $F(1, 11) = .271$, $p = .614$. There was no significant deviation from normality for the residuals of any of the seven dependent variables.

However, the significant effects reported above are based on absolute values, and must be considered in context. If proportionality of processing demands is considered, it would be expected that the 8x8 decision would take four times as long to make and require four times as many acquisitions as the 4x4 condition for equivalent amounts of processing. When predicted measures of TdTIME and ACQ for the 8x8 condition were compared against the actual values, the 8x8 condition took significantly less time and made significantly fewer acquisitions than would be predicted from the 4x4 baseline, $t(11) = -4.93, p < .001$, and $t(11) = -6.32$, $p < .001$ respectively.

In addition, proportionality between the decisions for PTMI must be considered. The PTMI for the low complexity, 4x4 condition was no different than would be expected if processing were distributed equally across the 4 attributes (25%). However, in the 8x8 condition, participants spent 20.5% longer on their subjectively most important attribute than would be expected (33% actual vs. 12.5% expected). Thus, on closer inspection, it is clear that the selectivity on PTMI was greater in the high complexity condition.

6.2.4 A comparison of the medical and the holiday decision domains under decision complexity

A repeated measures MANOVA of complexity (4x4, 8x8) by decision domain (medical, holiday) for the transformed dependent variables (TdTIME, ACQ, TperACQ, VARALT, VARATT) and the variables PTMI and PATTERN revealed a main effect of complexity

$F(7, 38) = 10.30, p < .001$. This arose through effects in TdTIME, $F(1, 10) = 15.13, p < .001$, ACQ, $F(1,10) = 36.99, p < .001$, and TperACQ, $F(1,10) = 27.90, p < .001$.

Table 6.3 Mean dependent measures by decision domain for the 4x4 decision

	Medical	Holiday
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	61.73 (43.17), 16.42 – 180.72	47.47 (36.02), 6.96 – 164.32
ACQ	38 (20.65), 13 - 87	35 (23.02), 6 – 132
TperACQ (ms)	879 (295.53), 510.40 – 1426.10	525 (176.43), 180.60 – 957.50
PTMI	.25 (.08), .13 – .40	.31 (.13), .12 – .69
	Measures of selectivity	
VARALT	.031 (.016), .001 - .048	.017 (.016), .001 - .050
VARATT	.017 (.069), 0 - .240	.016 (.017), .001 - .081
	Measure of information acquisition	
PATTERN	.113 (.410) -.739 - 684	.197 (.418), -.667 – 1.0

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

There was a significant interaction between complexity and decision domain, $F(7,38) = 2.66, p = .024$; specifically in terms of TperACQ, $F(1, 10) = 11.23, p = .002$, and PTMI, $F(1, 10) = 7.12, p = .011$. A series of unrelated and related t-tests of decision domain and complexity were conducted on these variables, to explore them further. There were significant differences between medical and holiday domains on TperACQ4, $t(46) = 5.05$, $p < .001$, TperACQ8, $t(46) = 3.45, p = .001$, and PTMI8, $t(46) = 2.60, p < .012$. There were no significant differences between decision domains on PTMI4, $t(46) = -1.21, p < .273$.

Thus, these interaction effects between decision domain and complexity on TperACQ and PTMI indicate that in terms of increasing complexity, participants making decisions in different domains responded differently in terms of TperACQ and PTMI.

Table 6.4 Mean dependent measures by decision domain for the 8x8 decision

	Medical	Holiday
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	124.53 (89.68), 13.40 – 263.80	69.72 (47.27), 15.33 – 234.71
ACQ	96 (72.9), 10 – 226	67 (49.9), 15 – 220
TperACQ (ms)	665 (218.84), 316.50 – 1080.30	477 (142.04), 156.90 – 896.70
PTMI	.33 (.25), .33 – 1.0	.18 (.09), 0 – .38
	Measures of selectivity	
VARALT	.013 (.013), .002 - .040	.017 (.014), .001 - .063
VARATT	.018 (.030), 0 - .110	.016 (.046), .001 - .281
	Measure of information acquisition	
PATTERN	.001 (.479), -.800 - .732	.298 (.388), -.571 – 1.0

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

6.3 Discussion

This study aimed further to explore the predictions of the Effort-Accuracy framework (E-Af, Payne *et al.*, 1993) in terms of increased cognitive economy as a response to increased cognitive demand. Specifically, this study aimed to explore if the information acquisition process underlying decision making became more streamlined in terms of amount of processing, selectivity, and the pattern of the search in the face of increasing decision complexity as defined by a four-fold increase in decision space. The results of this study provide support for increased cognitive economy in response to an increase in decision complexity, specifically in terms of the amount of information processed (both in absolute and relative terms). As complexity increased, participants spent proportionally less time making their decision, made proportionally fewer acquisitions, spent less time on each acquisition, and spent significantly more time acquiring information about their subjectively most important attribute. Thus, the results of this study are consistent with the predications of the E-Af (Payne *et al.*, 1993): increased task demand, in the face of a finite amount of cognitive resources, led to cognitive economy in the form of a decreased amount of information processed and more selective acquisition.

This study also aimed to explore decision domain effects on information processing; specifically, it set out to examine if the information acquisition process differed in a decision space of identical size, but set in a different subject domain. While the task in Study 1, Chapter 2 consisted of selecting a hotel for a holiday, the decision task in this study was selecting which patient should be seen first in an A&E setting. The results suggest that there were decision domain differences in response to complexity, in two cognitively optimal populations. While both participant populations in Study 1 and in this study demonstrated increased cognitive economy in response to increased task demand, they responded differently in terms of measures of amount of processing. Regardless of complexity, the medical participants spent longer making acquisitions than the participants in the holiday domain task. As complexity increased, medical participants spent significantly less time on each acquisition, while there was no significant change in the amount of time spent on each acquisition for the holiday group. In terms of the amount of time spent on the subjectively most important attribute, another measure linked to the amount of processing, the pattern was reversed between groups. As complexity increased, participants in the holiday domain became less selective in terms of their subjectively most important attribute; conversely, those in the medical domain became increasingly more selective. Thus, in the face of increasing complexity, those in the medical group accelerated their processing by reducing time per acquisition, and became more selective in considering attribute information in terms of subjectively-judged importance. Arguably, the medical domain resulted in more extreme cognitive streamlining than did the holiday domain. These results support the idea of decision domain differences, previously demonstrated through differences in patterns of decision outcome and preference reversals in the medical domain compared to analogous decisions of other domains (Redelmeier & Shafir, 1995; Redelmeier & Tversky, 1990, 1992). However, this is the first study focusing on decision domain differences in terms of the underlying information acquisition processes. This has important implications for the interpretation of decision making research. If decision domain differences exist, this would be a considerable confounding variable in comparing findings across research into decision making.

It is difficult, at this point, to determine the nature of these decision domain differences; i.e. if they represent quantitative or qualitative changes. It is possible that these results reflect quantitative differences in the computational demand of the decisions, rather than qualitative decision domain differences. Every effort was made to maintain an equivalent level of demand across both domains, and the decisions were consistent in terms of decision space size, a critical determinant of complexity in previous research (Hogarth, 1975; Payne, 1976, 1982). While estimating the cognitive demand of a certain task is difficult, for the purpose of exploratory research in this area such equivalence has previously been deemed acceptable (Redelmeier & Shafir, 1995; Redelmeier & Tversky, 1990, 1992). Thus, it is argued that these decisions may be considered analogous in terms of structural load. In future research, it may be beneficial to ask participants to rate the complexity of each decision, to gain some insight into their perceived, subjective experience of demand. At the very least, even if the different decisions did represent different levels of computational demand on a unitary scale, this study would provide additional support for the concept of a hierarchy of adaptivity, where the precise match between demand and resources results in a specific cognitive response.

On the other hand, it is possible that the decisions in both the holiday and medical domains were structurally equivalent in terms of demand, and it was the context in which they were set that altered the decision process. This possible qualitative difference, relating to topic and not decision structure, should be further explored in future research. In addition, other issues relating the nature of the medical domain versus other domains must be considered. This will be discussed further in Chapter 10.

The final aim of this study was to provide a baseline within the domain of medical decision making, to explore the effects of expertise on decision making. While a decision task in a field such as medicine requires some knowledge, the students who formed the participant group in this study could not be considered to be medical experts (Chase & Simon, 1973; Chi *et al.*, 1988; Ericsson & Smith, 1991; Hayes, 1985). Subsequent research in this thesis will replicate the study outlined in this chapter in a sample of medical experts; specifically, Study 6, Chapter 7, will explore the effects of expertise on increased decision complexity. The next chapter will continue to examine decision domain difference, in terms of increased task difficulty.

Chapter 7.

Study 6: Examining the effects of decision domain and decision difficulty on the information acquisition process underlying decision making

7.0 Introduction

This study had three objectives. First, it aimed further to examine the effects of an imbalance between task demand and task resources, in terms of a hierarchy of adaptivity which would be consistent with the predictions of the Effort-Accuracy framework (E-Af; Payne, Bettman, & Johnson, 1993). While the previous study operationalised increased task demand through increased task complexity, this study focussed on the effects of increased decision difficulty (operationalised by time pressure) as a mechanism of increased demand. Essentially, this study served as a replication of Study 2, Chapter 3, in another cognitively optimally population, with a different decision domain. As outlined in Study 2, Chapter 3, time pressure is an external factor that determines the level of task demand. Competing theories of the effects of time pressure on information acquisition in decision making suggest cognitive economy takes the form of acceleration (Ben-Zur & Breznitz, 1981), filtration (Miller, 1960), or a complete shift in decision strategy, in terms of a reduced amount of processing, increased selectivity, and a shift towards more attribute-led processing (Payne *et al.*, 1993). Study 2 found that time pressure resulted in a decrease in the amount of processing, and found support for the theory of acceleration of processing (Ben Zur & Breznitz, 1981). These results were consistent with the prediction of the E-Af, as well as those of the Yerkes-Dodson stress principle.

Second, the study reported in this chapter aimed further to explore decision domain effects, by comparing the effects of time pressure on the information acquisition process in a medical domain with a holiday domain. The previous chapter reported decision domain differences in response to increased complexity: participants in the medical domain exhibited a greater degree of cognitive streamlining than the participants in the holiday domain. As mentioned above, increased time pressure in a holiday decision domain led to acceleration and reduction in the amount of processing in a cognitively optimal population. If there are no differential effects of domain, it may be expected that this pattern of acceleration will occur in a medical decision of equivalent size and decision difficulty. However, if decision domain is a critical factor, as the previous study suggests, there may be alternative effects on the information acquisition process. Rather than cognitive streamlining in the form of acceleration, as seen in Study 2, Chapter 3, it may be evident either in the form of filtration (Miller, 1960), or a broad shift in decision strategies (Payne *et al.*, 1993).

Third, this study aimed to provide a baseline for the examination of the balance between enhanced resources (operationalised by medical expertise) and time pressure, which will be explored in Study 8, Chapter 9.

7.1 Method

7.1.1 Participants: The same 12 University of Southampton medical students (6 males, 6 females, age *M* 22 years, *SD* 1.5, range 18 - 26) who participated in Study 5, Chapter 6 participated in this study.

7.1.2 Stimuli/Procedure: The stimuli in this study were the same sets of decisions presented via the Mouselab software that were used in Study 5. Time pressure was operationalised by asking participants to complete the decision task as quickly as possible: it was emphasized that a rapid response time was critical. During the task, a clock face with a ticking second hand was present in the corner of the computer screen to reinforce the urgency message. The procedure in this study was the same that of Study 5, except that participants were asked to rate their subjective experience of time pressure as a manipulation check, on a scale of 1 – 3 (1 = a lot, 2 = moderate, 3 = none).

7.1.3 Dependent measures: The dependent measures in this study were the same seven previously published measures as those used in all previous studies: relating to amount of processing (TdTIME, ACQ, TperACQ, PTMI), selectivity (VARALT, VARATT), and pattern of search (PATTERN).

7.1.4 Analysis: The data analysis procedure broadly followed that outlined in Study 2, Chapter 3, Section 3.1.4. To examine the differential effects of complexity and difficulty, the data were compared against those in the previous study, Study 5. In addition, to examine the effect of decision domain, a repeated measures MANOVA of difficulty (time pressure low vs. high) and decision domain (medical vs. holiday) was conducted on the transformed variables. A series of non-parametric tests, between and within decision domains, was conducted to explore any interactions.

7.2 Results

All data except PATTERN values were log transformed due to positive skew. None of the variables was excluded on the grounds of co-linearity (see Table 7.2). Tables 7.1, 7.2 – 7.5 contain raw score descriptives, for ease of interpretation. A manipulation check for time pressure revealed that the median rating for this participant group was 1 (range 1-3), indicating that the group felt a high level of time pressure in the time pressure condition.

7.2.1 The 4x4 condition:

As outlined in Study 5, Chapter 6.

7.2.2 The 4x4 time pressure condition:

In the 4x4 time pressure condition, if every item were considered, the duration and number of acquisitions for each item would average at 2.9s and 2 respectively. If this is factored out in terms of alternatives, this would average out at 11.4s and 8 acquisitions per alternative. Participants spent, on average, 46% of the total decision time considering values of their subjectively-determined most important attribute (PTMI). This was significantly longer than expected if time were distributed equally across attributes (25%), $t(11) = 3.96$, $p = .002$. The amount of processing in this condition suggests a

Table 7.1 Mean dependent measures by decision condition

	4x4	4x4 time pressure
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	61.73 (43.17), 16.42 – 180.72	45.57 (34.01), 17.80 –131.20
ACQ	38 (20.7), 13 – 87	32 (21.2), 14 – 85
TperACQ (ms)	879 (295.53), 510.40 – 1426.10	702 (217.13), 396.40 – 1256.80
PTMI	.25 (.08), .13 – .40	.46 (.18), .26 – .75
	Measures of selectivity	
VARALT	.031 (.016), .001 - .048	.008 (.006), .001 - .022
VARATT	.017 (.069), 0 - .240	.027 (.029), 0 - .089
	Measure of information acquisition	
PATTERN	.113 (.410), -.739 - .684	-.001 (.444), -.526 – 1.0
% acquisition time	56	51

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME.

moderate level of demand. In terms of the pure measures of selectivity, VARATT indicates that participants were using a largely consistent search pattern, whereas VARALT indicated a moderately selective search pattern across alternatives (Payne, Bettman, & Johnson, 1988).

Table 7.2 Correlation matrix for dependent variables: 4x4 above the diagonal, 4x4 time pressure below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.51	.13	-.09	-.43	-.35	.06
ACQ	.78‡		-.09	-.13	-.28	-.49	.18
TperACQ	.42	.27		-.40	.03	-.06	.30
PTMI	-.35	-.29	-.09		-.18	.29	.12
VARATT	-.42	-.39	-.06	.73‡		.09	-.27
VARALT	-.51	-.51	-.34	.09	.13		-.19
PATTERN	-.13	-.25	.44	-.31	-.18	-.43	

Note. † = $p < .05$ level (2 tailed); ‡ = $p < .01$ level (2 tailed)

In terms of PATTERN, the search was neither more alternative nor more attribute-led, compared to a consistent search value of 0, $t(11) = -0.01$, $p = .995$.

7.2.3 A comparison of the 4x4 and 4x4 time pressure conditions:

Interestingly, as under complexity, this group of participants did not appear to search consistently between conditions (low and high difficulty), although there is some indication they are searching consistently across demand source conditions (complexity vs. difficulty) (see Table 7.2). As with complexity, there are no correlations under low difficulty. Under high difficulty, TdTIME is positively correlated with ACQ, which is the most common correlation seen across the studies reported herein. In addition, under high difficulty, PTMI is positively correlated with VARATT, which is logical according to the E-Af.

A repeated measures MANOVA of difficulty (4x4, 4x4 time pressure) for the transformed dependent variables (TdTIME, ACQ, TperACQ, PTMI, VARALT, VARATT) and the variable PATTERN revealed no main effect of difficulty, $F(7, 4)$ - = 4.92, $p = .109$. There were, however, significant differences of difficulty in TdTIME, $F(1, 11) = 9.96$, $p = .012$, and in PTMI, $F(1, 11) = 16.91$, $p = .003$. No significant effects for difficulty were found for ACQ, $F(1, 11) = 1.26$, $p = .290$, VARATT, $F(1, 11) = 3.67$, $p = .087$, VARALT, $F(1, 11) = .88$, $p = .374$, and PATTERN, $F(1, 11) = .50$, $p = .496$.

TperACQ approached significance, $F(1, 11) = 4.70$, $p = .058$. There was no significant deviation from normality for the residuals of any of the dependent variables. Thus, participants processed less information, but were not more selective in their information acquisition, and did not change their search pattern to a more non-compensatory attribute-led pattern under time pressure. The ratio of acquisition time to deliberation time was not significantly different across conditions, $t(11) = 0.91$, p = .384.

7.2.4 A comparison of the difficulty (4x4 time pressure) and complexity (8x8) conditions:

To account for decision size differences, variables relating to the amount of processing which are susceptible to decision size (TdTIME, ACQ, PTMI) for both difficulty (4x4 time pressure) and complexity (8x8) conditions were transformed into ratio values in terms of their baseline 4x4 values, e.g. TdTIME 8x8/TdTIME 4x4 and TdTIME 4x4 time pressure/TdTIME 4x4 (see Table 7.3). A series of paired t-tests for these transformed values revealed significant differences in computational type (complexity vs.

Table 7.3 Transformed ratio values for amount of processing measures

	4x4 time pressure	8x8
	Ratio measures of information processing	
	M (*SD*)	*M* (*SD*)
rTdTime (s)	.77 (.33)	2.08 (1.27)
rACQ	.94 (.47)	2.74 (1.85)
rPTMI	2.04 (1.06)	1.61 (1.97)

Note. rTdTime = total time to decision ratio; rACQ= ratio of number of information boxes examined; rTperACQ = time per information acquisition ratio; rPTMI = ratio of proportion of time spent on subjectively most important attribute

difficulty) for TdTIME, $t(11) = -3.34, p = .007$; and ACQ, $t(11) = -3.47, p = .005$. There was no significant difference for PTMI, $t(11) = 0.78, p = .452$. Thus, complexity as the demand source led to a significantly longer average total decision time, and a significantly greater number of acquisitions than difficulty. There was no significant difference between complexity and difficulty in the amount of time spent on the most important attribute.

A repeated measures MANOVA of decision type (4x4 difficulty, 8x8 complexity) for the transformed dependent variables revealed no main effect of decision type, $F(4,7) = 1.07$, $p = .435$. Specifically, of the variables that are not susceptible to decision size effects (TperACQ, VARALT, VARATT, PATTERN), there were no significant effects for decision type for, TperACQ, $F(1,11) = 0.931, p = .357$, VARATT, $F(1,11) = 1.58$ $p = .237$, VARALT, $F(1,11) = 0.68, p = .426$, or PATTERN, $F(1,35) = 0.02, p = .888$. Participants did not differ in the amount of time per acquisition, the selectivity, or type of search pattern in the face of different computational demand sources.

7.2.4 A comparison of the medical and the holiday decision domains under time pressure

A repeated measures MANOVA of difficulty (4x4, 4x4 time pressure) by decision domain (medical, holiday) for the transformed dependent variables (TdTIME, ACQ,

Table 7.4 Mean dependent measures by decision domain for the 4x4 decision (young participant groups)

	Medical	Holiday
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	61.73 (43.17), 16.42 – 180.72	47.47 (36.02), 6.96 – 164.32
ACQ	38 (20.65), 13 - 87	35 (23.02), 6 – 132
TperACQ (ms)	879 (295.53), 510.40 – 1426.10	525 (176.43), 180.60 – 957.50
PTMI	.25 (.08), .13 – .40	.31 (.13), .12 – .69
	Measures of selectivity	
VARALT	.031 (.016), .001 - .048	.017 (.016), .001 - .050
VARATT	.017 (.069), 0 - .240	.016 (.017), .001 - .081
	Measure of information acquisition	
PATTERN	.113 (.410) -.739 - 684	.197 (.418), -.667 – 1.0
% acquisition time	54	38.7

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME x 100).

TperACQ, PTMI, VARALT, VARATT) and the variable PATTERN revealed a main effect of difficulty $F(7, 38) = 3.33, p = .007$. This arose through effects in TdTIME, $F(1,44) = 14.50, p < .001$, ACQ, $F(1, 44) = 7.66, p = .008$, TperACQ, $F(1, 44) = 8.92, p$ =

.005, and in PTMI, $F(1, 44) = 10.45, p = .002$. In addition, there was a main effect of decision domain, $F(7, 38) = 8.90, p < .001$. This arose through main effects of decision domain, for TdTIME, $F(1, 44) = 4.21, p = .046$, and TperACQ, $F(1, 44) = 31.37, p < .001$.

Table 7.5 Mean dependent measures by decision domain for the 4x4 time pressure decision

	Medical	Holiday
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	45.57 (34.01), 17.80 – 131.20	28.18 (29.19), 3.13 – 177.18
ACQ	32 (21.2), 14 - 85	25 (16.08), 5 – 68
TperACQ (ms)	702 (217.13), 396.40 – 1256.80	417 (168.12), 167.80 – 843.60
PTMI	.46 (.18), .26 – .75	.29 (.16), .09 – 1.0
	Measures of selectivity	
VARALT	.030 (.006), .001 - .022	.019 (.032), .001 - .187
VARATT	.027 (.029), 0 - .089	.027 (.035), .001 - .187
	Measure of information acquisition	
PATTERN	-.001 (.444) -.526 – 1.0	.175 (.477), -1.0 – 1.0
% acquisition time	51	37

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME x 100).

There was a significant interaction between difficulty and decision domain, $F(7, 38) = 3.26, p = .008$; specifically in terms of PTMI, $F(1, 44) = 16.29, p < .001$. Two unrelated t-tests of decision domain and difficulty were conducted on these variables, to explore them further. There was a significant difference between medical and holiday domains on PTMI8 under time pressure, $t(46) = 3.23$, $p = .002$, and no significant difference between decision domains on PTMI4 (no time pressure), $t(46) = -1.21$, $p = .233$.

Thus, these interaction effects indicate that there are domain differences in how much time was spent in the most subjectively important attribute in the face of increasing difficulty. When decision difficulty was low, participants in each domain were no more selective in terms of their most important attribute (PTMI); however, in the high difficulty condition, the medical domain participants spent significantly longer in their subjectively most important attribute. Thus, in the face of increasing time pressure, participants in the medical decision domain become increasingly selective, while those in the holiday decision did not.

7.3 Discussion

This study had several aims; first, it aimed to further explore the effects of increasing task demand through increased decision difficulty on the information acquisition process, and to examine to what extent the results were consistent with the predictions of the Effort-Accuracy framework (E-Af; Payne *et al.*, 1993). As outlined in earlier chapters, the E-Af predicts that as task demand increases, decision makers adopt cognitive economy through decreasing the amount of information processed, becoming more selective in their search, and adopting more attribute-led patterns of search. These results provide some support for this trend of cognitive streamlining as difficulty increased: specifically, participants reduced the amount of processing they performed under time pressure. They took significantly less time to make the decision, and spent more time considering their selectively most important attribute. Arguably, these results also provide support for the theory of acceleration (Ben Zur & Breznitz, 1981), as there was a trend towards making each acquisition more rapidly under time pressure. As outlined in Study 2, Chapter 3, the theory of acceleration specifies that roughly the same amount of information is processed (i.e. same number of items accessed), simply at a more rapid rate. The results of this study are arguably consistent with this, as the ratio of acquisition time to deliberation time was equivalent across conditions and the number of acquisitions did not differ significantly across conditions. An equivalent number of items were acquired, but with fewer repetitions: items were not accessed as frequently, and considered for less time. Thus, while these results provide some support for the theory of acceleration (Ben Zur & Breznitz, 1981), evidence for acceleration is not as clear as it was in the young holiday decision domain group. In addition, arguably the results can distinguish acceleration as a strategy in its own right, from a wider shift to non-compensatory strategies, as demonstrated by Payne *et al.* (1993). This distinction is possible as, in addition to the acceleration of processing, participants were more selective in terms of acquiring information about their subjectively most important attribute. This measure is related to a broad shift to non-compensatory, cognitively-economical, decision strategies (Payne *et al.*, 1993). Thus, while in Study 2, it was hard to distinguish between a stand-alone strategy of acceleration or a broader non-compensatory strategy such as those outlined in Chapter 1, the results of this study provide more support for the latter. Participants were not just processing information more quickly, they modified their processing according to the subjective importance of different attributes. As in Study 2, there was no evidence for filtration (Miller, 1960) in terms of selectivity of search across attributes and alternatives.

The second aim of this study was to examine the effects of decision domain on the information acquisition process in the face of increasing task difficulty, i.e. increased time pressure. In the previous study, in response to increased task complexity, decision domain differences were found between holiday and medical decisions of equivalent demand. This study provides additional evidence for domain effects on the information acquisition process: specifically, in terms of how much time participants spent considering information from their subjectively most important attribute. When decision difficulty was low, there was no difference between the holiday and medical participant groups in terms of how much time they spent in this attribute. However, as time pressure increased, the medical participant group became more selective, spending significantly more time acquiring information on their subjectively most important attribute. The holiday participant group did not become more selective in the face of increased time pressure. Thus, decision domain appears to have an effect on the information acquisition process.

Decision domain differences can also be seen across the different types of demand source. In the holiday domain, increased complexity led to a reduction in the amount of processing through a proportional reduction in decision time, a proportional reduction in the number of acquisitions, and an increase in time spent in the subjectively most important attribute. However, increased decision difficulty led to a reduction in total decision time and a reduction in the number of acquisitions, and instead of greater selectivity in terms of the most important attribute, it led to more rapid acquisitions. Thus, in the holiday domain, there were demand source differences in the response to increased task demand: participants responded differently to increased complexity than they did to increased difficulty. Generally, in a cognitively-optimal population in a holiday decision domain, complexity appeared to be more cognitively-demanding (led to more cognitive-economy) than did difficulty.

In the medical domain, on the other hand, both types of demand source led to the same response: reduced decision time, more rapid acquisitions, and an increase in the selectivity of processing on the subjectively most important attribute. Arguably, the medical domain led to a greater reduction in the amount of information processed, regardless of demand source. This provides additional support for the importance of recognising different domains, initially raised by research examining outcome and preference reversals (Redelmeier & Shafir, 1995; Redelmeier & Tversky, 1990, 1992). These results suggest that it is not simply structural factors that determine task complexity, but that decision domain effects must be considered. As mentioned in the previous chapter, further research must be conducted to discern if decision domain differences are due to quantitative or qualitative factors. This will be discussed further in Chapter 10.

The results of this study may also be considered consistent with the proposed hierarchy of adaptivity, in which the cognitive response to increased task demand (i.e. the type of strategy employed) is determined by the nature of the balance between task demand and the cognitive resources available to apply the task. Decision domain differences hint at the fact that, while the decisions are computationally equivalent in terms of size, a medical domain may be slightly more qualitatively computationally demanding than a holiday domain. Potential differences between domains are discussed further in Chapter 10. This is suggested in the greater reduction in the amount of processing in the medical domain studies, regardless of demand source. However, this difference is slight, and does not translate into more extreme forms of cognitive economy such as selectivity or a shift in pattern. Thus, this slight difference in information acquisition across domains suggests that a hierarchy of adaptivity is, indeed, very sensitive to the precise balance between demand and resources.

This study, along with that reported in the previous chapter, forms the baseline to examine the effects of enhanced resources, operationalised by expertise, on decision making. The next two chapters will examine the effects of decision complexity and difficulty in a population with enhanced cognitive resources.

Chapter 8.

Study 7: Examining the effects of increased decision complexity on the information acquisition process underlying decision making in a population with enhanced cognitive resources

8.0 Introduction

According to the Effort-Accuracy framework (E-Af; Payne, Bettman, & Johnson, 1993), the precise balance between task demand and the cognitive resources available to apply to that task determines what decision strategies will be employed. Throughout the course of this thesis, the hierarchy of adaptivity that is inferred from the E-Af is explored through manipulating the balance between demand and computational availability. In Chapters 4 and 5, the effects of diminished cognitive resources in the face of increasing task demands was explored in relation to increased demand in a cognitively-normal (healthy, younger adult) population. The older adult population represented an increase in the mismatch between task demand and computational availability, compared to the baseline younger adult group. Conversely, in the next two chapters, the effect of enhanced cognitive resources (operationalised by expertise) on the information acquisition process will be explored, in relation to a cognitively-normal population within the same decision domain. This represents a reduction in the mismatch between task demand and computational availability.

Expertise is considered to be an exceptional competence relying on internal knowledge structures (Hakkarainen, 2002), and it is thought to reduce task demand by minimizing demands on working memory through an increased declarative, or crystallised, knowledge base (Yekovich, Walker, Ogle, & Thompson, 1990). According to this view, while working memory, or fluid intelligence, remains unchanged by expertise, domain-specific, crystallised knowledge allows the expert to use their working memory more effectively. This may take place in the form of the ability to be more selective or to form larger chunks of information (Liu, Schallert, & Carroll, 2004), or it may even occur through 'outsourcing' cognitive activity to other parts of the brain; for example away from Broca's area, which is associated with working memory, to cortical areas relating to visuo-spatial working memory in a digit recall task (Tanaka, Michimata, Kaminaga, Honda, & Sadato, 2002). Some researchers even suggest that high levels of expertise are associated with expanded working memory capacities (Takagi, 1997). Working memory is the main, if not sole, component of cognitive resources (Kahneman, 1973). Whether it is the efficiency or the capacity of working memory that is increased, there can be little argument that expertise leads to enhanced cognitive resources.

To date, research into expertise and decision making has been rooted in the heuristics and biases approach initiated by Kahneman and Tversky in the 1970s. As such, much research has been conducted on the effects of framing, biases, and preference reversals (Arkes, Wortmann, Saville, & Harkness, 1981; Bazerman, Loewenstein, & Moore, 2002; Camerer & Johnson, 1991; Koehler, Brenner, & Griffin, 2002; McNeil, Pauker, Sox, & Tversky, 1982). One of the main findings, across many areas of expertise, is that domain expertise reduces bias in decision making (Bornstein, Emler, & Chapman, 1999; Cohen, 1993; Keren, 1987; Shanteau, 1989). Such findings in relation to medical expertise demonstrate that medical staff endorse sunk cost reasoning, where continued investment occurs after an initial investment in the face of poor returns, less on medical decisions than on non-medical ones. Within the context of the heuristics and biases research program, researchers acknowledge that experts are able to form new strategies when required (Glaser, 1996), although these strategies are not explicitly related to information acquisition underlying decision making. The heuristics and biases approach also recognises that experts have richer mental models, or representations of how things work, than novices (Rouse & Morris, 1986). They recognise that experts have a larger source of declarative knowledge (both explicit and tacit) than do novices (Anderson, 1983), and are able to use this knowledge to run mental simulations of possible decision outcomes (Einhorn & Hogarth, 1981). However, the heuristics and biases approach did not consider how the knowledge experts hold affects what knowledge they seek in new decisions, i.e. how information acquisition in a particular decision space is affected by existing and established knowledge structures. Specifically, in terms of information processing, very little work has been conducted to examine the types of decision strategies that experts employ, and how these change in different decision environments or circumstances.

In more recent times, a model of decision making called the Recognition-Primed Decision model (RPD; Klein, 1998; Klein, Calderwood, & Clinton-Cirocco, 1986) has provided the basis for a few studies to examine the effect of expertise on information processing; despite this, it remains an area that is largely neglected. The RPD examined issues of representation and process that had previously been ignored (Smith & Osherson, 1989). It assumes that, in naturalistic decision settings, experts rely on their extensive knowledge base to make judgements and decide how to act. Thus, such knowledge affects information processing, in the sense that it alters how processing is conducted by experts in comparison to novices. In an early study, Klein and Brezovic (1986) found evidence for wide usage of the non-compensatory strategy of satisficing in situations where experts were not subject to time pressure.

In the field, the RPD approach has resulted in several findings with regard to the information processing underlying decision making; in other words, the types of strategies adopted by medical experts in domain-relevant decisions. Generally, the building of expert medical knowledge structures results in many different disease 'scripts:' this organisation of knowledge by scripts results in more rapid knowledge application (Boshuizen, Hobus, Custers, & Schmidt, 1993). Boshuizen *et al.* argue that this results in greater cognitive flexibility, i.e. the ability to modify hypotheses during diagnostic reasoning. This implies a greater flexibility of strategy use during decision making; however, as far as can be ascertained, this has not as yet been supported by research.

To date, very little research has examined the information acquisition process, in terms of decision strategies, in expert medical decision making. There is some evidence that medical practitioners use fast and frugal, i.e. non-compensatory, strategies when making treatment decisions (Hoffrage, Kurzenhauser, & Gigerenzer, 2005). In addition, research has demonstrated that doctors use only few cues, or a small amount of information available in the decision space, to make their treatment decision (Dhami & Harries, 2001). There is also some evidence that experts search decision spaces in a different manner to novices. Kundel and La Follette (1972) reported that expert radiologists searched and processed x-ray plates differently to novice radiologists: while the experts focused on certain areas and moved 'irrationally' around the plate, while novices scanned the entire plate in an ordered manner.

In other domains, the little work that has been conducted on information acquisition has found mixed results in relation to differences between experts and novices. Research has demonstrated that, in the context of expertise in car buying, experts did not search information in the decision space any differently than novices, but made better quality decisions with that information (Patrick, 1996). However, other research based on a naturalistic, audit judgement task found that experts employed more non-compensatory search strategies than did novices in a low task demand environment: the experts took less time, used fewer steps (i.e. fewer acquisitions) and searched less information (Salterio, 1996). However, none of these studies manipulated task demands to explore effects on the decision making process.

The study reported in this chapter aimed to examine the effects of increasing task demand (operationalised by complexity) on information acquisition in a population with enhanced cognitive resources. In terms of the E- Af (Payne *et al.*, 1993), this study aimed to examine the effects of minimising the discrepancy between task demand and computational availability. Broadly, the E-Af would predict that, as task demand increases, a population with enhanced resources will maintain compensatory, cognitively-effortful strategies for longer in the face of a rising level of task demand than a population with fewer resources. Thus, it is possible that as task demand increases, experts are better able to cope with the cognitive strain of more information (Enis, 1995), so may be able to consider most or all of the decision space in a normative, compensatory manner. On the other hand, they may experience cognitive strain, and as the E-Af predicts, experts may follow the pattern of adopting non-compensatory strategies in the face of increased demand as seen in the novice population in Study 5. Conversely, it has been claimed that expertise leads to more established, refined use of non-compensatory strategies, even when processing demands do not outweigh resources (Smith & Osherson, 1989). As such, it is possible that experts will employ cognitive economy even when there is no mismatch between task demand and task resources, by force of habit (Payne *et al.*, 1993).

Thus, it is possible that medical experts have sufficient resources, as complexity increases, to maintain normative, compensatory processing, which the E-Af would predict if resources outweigh task demands. It is also possible that their information processing patterns across conditions will mirror those of the novices, in that the experts will shift to more non-compensatory strategies as task demand increases. This would also be consistent with the predictions of the E-Af, particularly if the non-compensatory strategies employed by the experts were less severe than those employed by the novices. As predicted in previous studies, if the experts are overwhelmed by task demand in the high complexity condition, it is always possible they will suffer cognitive overload. This would also be in line with the predictions of the E-Af. However, given that the medical novices did not do so, this is unlikely.

Conversely, it is possible that expertise does not simply expand the pool of cognitive resources, but actually changes how these resources are employed. As such, the experts may be more likely to employ non-compensatory strategies, even in a low demand decision environment. This could be the result of habitual strategy use (see Payne *et al.,* 1993). This is not consistent with the predictions of the E-Af. In addition, it is also possible that experts are able to employ habitual strategies in the low complexity condition, but as complexity and task demand increase, they must make more effort and switch to more normative, compensatory strategies. Clearly, this should only occur if task demand does not outweigh the amount of resources available.

*Table 8.1 Possible outcomes and possible explanations when shifting from a low to a high complexity decision task (items with a * are consistent with the predictions of the E-Af, Payne et al., 1993)*

Possible outcomes	Possible explanations
1. Compensatory decision strategies	1a. Sufficient cognitive resources to cover task demand*
2. Non-compensatory strategies	2a. Shifts in knowledge structures change information processing
	2b. Insufficient resources, shift to cognitive economy (at a later point than novices)*
	2c. Sufficient resources but force of habit
3. Cognitive overload	3a. Adaptivity failure: cognitive system cannot conduct any organised search*
	3b. Habitual strategy usage leads to inappropriate strategy selection

8.1 Method

8.1.1. Participants: 12 Accident and Emergency (A&E) consultants (9 males, 3 female, *M* 41 years, *SD* 1.2, range 32 - 56), with a minimum of 10 years experience in an A&E setting participated in this study. A certain amount of clinical experience is necessary for an individual to be considered a medical expert, as domain knowledge informs practice but practice shapes knowledge (Patel, Arocha, & Kaufman, 1999). As enhanced resources due to expertise cannot necessarily be measured by working memory span, the standardized test of working memory span (Digits Backward, a subtest of the WAIS- III, Wechsler, 1997) was not administered here.

8.1.2 Stimuli/ Procedure: The stimuli in this study were the same sets of decisions presented via the Mouselab software that were used in Study 5, Chapter 6. The procedure followed was identical to that of Study 5.

8.1.4 Dependent measures: In this study, the seven previously published measures that were used in previous studies were used: relating to amount of processing (TdTIME, ACQ, TperACQ, PTMI), selectivity (VARALT, VARATT), and pattern of search (PATTERN).

8.1.5 Analysis: The data analysis followed that outlined in Study 3, Chapter 4, Section 4.1.4. In addition, to compare novice and expert decision makers, a repeated measures MANOVA of complexity (4x4, 8x8) and expertise level (novice, expert) was conducted on the transformed variables. A series of non-parametric tests, between and within age groups, was conducted to explore any interactions.

8.2 Results

All data except for the PTMI and PATTERN variables were log transformed due to positive skew. There were no issues of co-linearity between dependent variables (see Table 8.3). Tables 8.2, 8.4, and 8.5 contains raw score descriptives, for ease of interpretation.

8.2.1 The 4x4 condition:

If all items of information in the decision space were considered, this would average at 2.7s and 1.5 acquisitions per item. Factored out by alternative, this would average at 10.8s and 6 acquisitions per alternative. In a 16 item decision space, with 4 attributes in each alternative, this implies just over a single acquisition per item, that is, a low rate of repetition of acquisitions. The average amount of time per acquisition was quite high, at an average of more than two seconds for each acquisition. Participants spent on average 39% of the time on the subjectively most important attribute (PTMI), which was significantly more than the 25% of the time they should have spent if processing were equivalent across the 4 attributes, $t(11) = -3.56, p = .004$. In terms of information processing, the demands appeared to be moderate, with few acquisitions taking a considerable amount of time, and evidence of selectivity of processing.

Table 8.2 Mean dependent measures by decision condition

	4x4	8x8
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	42.60 (24.97), 16.86 – 92.25	97.48 (101.44), 21.28 – 403.99
ACQ	25 (18.0), 9 – 77	60 (50.90), 15 – 220
TperACQ (ms)	776 (305.05), 488.10 – 1518.20	644 (280.65), 287.60 – 1353.90
PTMI	.39 (.13), .24 – .71	.35 (.11), .17 – .55
	Measures of selectivity	
VARALT	.012 (.007), .001 - .022	.012 (.014), .001 - .055
VARATT	.017 (.023), .002 - .085	.013 (.001), .002 - .031
	Measure of information acquisition	
PATTERN	-.020 (.699), -.833 - .857	-.156 (.622), -1.0 – .808

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

In terms of selectivity of the search pattern, the search pattern was consistent and did not appear particularly selective across either attributes or alternatives (Payne, Bettman, & Johnson, 1988). The information acquisition pattern was neither significantly attribute nor alternative-led, compared to a neutral search pattern value of 0, $t(11) = -.101$, $p = .921$.

8.2.2 The 8x8 condition:

In the 8x8 condition, if every item were considered, this would average at 1.5s and 0.9 acquisitions per item. Across alternatives, this would average at 12.2s and 7.2

Table 8.3 Correlation matrix for dependent variables: 4x4 above the diagonal, 8x8 below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.80‡	.51	-.20	-.35	-.21	.06
ACQ	.71 ‡		-.01	-.23	-.32	-.23	.18
TperACQ	.74‡	-.75‡		.28	.14	.12	.30
PTMI	-.53	-.66†	-.32		.74 ‡	.54	.12
VARATT	-.54	-.67 †	-.35	.75‡		.52	-.27
VARALT	-.28	-.35	-.03	.61†	.56		-.19
PATTERN	.31	.34	.33	.48	-.59†	-.24	

Note. † = p <.05 level (2 tailed); ‡ = p < .01 level (2 tailed)

acquisitions. This implies that all information in the decision space was not examined. Participants spent 35% of the time considering information in their subjectively most important attribute (PTMI), which is significantly different to the 12.5% of the time they would have spent if processing demands were consistent across attributes, $t(11) = -7.01$, $p < .001$. In terms of information processing, the demand appears to be high: participants were not quite able to process information about all items in the decision space. In addition, there was evidence for selectivity of processing, in terms of PTMI. The search was not selective across attributes or alternatives (Payne *et al.*, 1988). In terms of PATTERN, the search was not significantly attribute-led, compared to a neutral search pattern value of 0, $t(11) = -0.87$, $p = .403$.

8.2.3 A comparison of the 4x4 and 8x8 conditions:

In terms of the comparison between patterns of correlation between variables (see Table 8.3), there are many more correlations between variables under the high complexity condition than under the low complexity condition. In terms of low complexity, TdTIME and ACQ, the most frequently seen correlation across groups and conditions, were positively correlated. In addition, PTMI was positively correlated with VARATT, indicating that more selective searches were associated with more time spent in the subjectively most important attribute.

In terms of the high complexity condition, TdTIME was again positively correlated with ACQ, and also with TperACQ. ACQ and TperACQ were also highly positively correlated, which indicates that overall decision time was dependent on both the number and duration of acquisitions, and that when more acquisitions were made, they tended to last longer. ACQ was also negatively correlated with PTMI and VARATT, which indicates that as a search involved more time in the subjectively most important attribute, and was more selective, it involved fewer acquisitions. This is supported by the fact that PTMI was positively correlated with VARATT and VARALT. In addition, in the high complexity condition, PATTERN was negatively correlated with VARATT, indicating that a more selective search was related to a more non-compensatory search.

Table 8.4 Mean dependent measures by expertise level for the 4x4 decision

	Novices	Experts
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	61.73 (43.17), 16.42 – 180.72	42.60 (24.97), 16.86 – 492.25
ACQ	38 (20.65), 13 – 87	25 (18.0), 9 – 77
TperACQ (ms)	879 (295.53), 510.40 – 1426.10	776 (305.05), 488.10 – 1518.20
PTMI	.25 (.08), .13 – .40	.39 (.13), .24 – .71
	Measures of selectivity	
VARALT	.031 (.016), .001 - .048	.012 (.007), .001 - .022
VARATT	.017 (.069), .000 - .240	.017 (.023), .002 - .085
	Measure of information acquisition	
PATTERN	.113 (.410), -.739 - .684	-.020 (.699), -.833 – .857

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

A repeated measures MANOVA of complexity (low, high) was carried out for the transformed variables (TdTIME, ACQ, TperACQ, VARALT, VARATT) and the variables PTMI and PATTERN and revealed a main effect of complexity, $F(7,5) = 5.38$, $p = .041$. This arose through significant effects of complexity in TdTIME, $F(1, 11) =$

10.57, $p = .008$, ACQ, $F(1, 11) = 17.25$, $p = .002$, and TperACQ, $F(1, 11) = 7.71$, $p = .018$ No significant effects of complexity were found in PTMI, $F(1, 11) = 1.38$, $p = .264$, VARATT, $F(1, 11) = 1.66$, $p = .692$, VARALT, $F(1, 11) = .77$, $p = .398$, or PATTERN, $F(1, 11) = 2.34$, $p = .154$. There was significant deviation from normality for the residuals of 2 variables, both from the 4x4 condition (PTMI and PATTERN). Non-parametric comparisons of complexity level were conducted. As in the MANOVA, there were consistently no significant effects of complexity on PTMI, $Z(N=12) = -.84$, $p = .388$, or on PATTERN, $Z(N=12) = -1.60$, $p = .110$.

Table 8.5 Mean dependent measures by expertise level for the 8x8 decision

	Novices	Experts
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	124.53 (89.68), 13.40 – 263.80	97.48 (101.44), 21.28 – 403.99
ACQ	96 (49.90), 15 –220	60 (50.90), 15 – 200
TperACQ (ms)	665 (218.84), 316.50 – 1080.30	644 (280.65), 287.60 – 1353.90
PTMI	.33 (.25), .33 – 1.0	.35 (.11), .17 – .55
	Measures of selectivity	
VARALT	.031 (.013), .002 - .040	.012 (.014), .001 - .055
VARATT	.018 (.030), 0 - .110	.013 (.001), .002 - .031
	Measure of information acquisition	
PATTERN	.001 (.479), -.800 - .732	-.156 (.622), -1.0 – .808

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

However, as in Studies 1, 3 and 5, proportionality between conditions for TdTIME, ACQ, and PTMI must be considered. Given the baseline TdTIME of this group for the 4x4 condition, this would predict a TdTIME of 170.4s on the 8x8 condition, if processing demands were maintained across conditions. In fact, TdTIME in the 8x8 condition was significantly less than this, at 97.5s, $t(11) = -4.26$, $p = .001$. Similarly, the actual number of acquisitions on the 8x8 condition was significantly less than the predicted value of 98 (4 x ACQ4), $t(11) = -3.17, p = .009$. In terms of PTMI in the 4x4 condition, participants spent 14% more time in their subjectively most important attribute than an equal division of attention across attributes would predict (39% vs. 25%). In the 8x8 condition, participants spent 22.5% more time in the PTMI than they would have if processing demands had been equal across all 8 attributes (35% vs. 12.5%). So, while the statistical analysis appears to suggest that selectivity in terms of the subjectively most important attribute was greater in the 4x4 condition, when proportionality is considered, selectivity was actually greater in the 8x8 condition.

8.2.4 A comparison of expertise levels and decision complexity

A repeated measures MANOVA of complexity (4x4, 8x8) by expertise level (novice, experts) for the transformed dependent variables (TdTIME, ACQ, TperACQ, VARALT, VARATT) and the variables PTMI and PATTERN revealed a main effect of complexity $F(7, 15) = 9.01, p < .001$. This arose through effects in TdTIME, $F(1,21) = 15.28, p = .001$, ACQ, $F(1,21) = 22.03, p < .001$, and TperACQ, $F(1,21) = 25.12, p < .001$. There was no main effect of expertise level, $F(7,15) = 1.10, p = .416$. Specifically, there were no effects of expertise level in TdTime, $F(1, 21) = 1.33, p = .265$, ACQ, $F(1, 21) = 2.67, p = .117$, TperACQ, $F(1, 21) = .778, p = .388$, PTMI, $F(1, 21) = 2.28, p = .146$, VARATT, $F(1, 21) = .00, p = .978$, VARALT, $F(1, 21) = .00, p = .969$, and PATTERN, $F(1, 21) = .48, p = .498$. There were also no interaction effects between decision complexity and expertise level, $F(7, 15) = .85, p = .562$.

8.3 Discussion

This study broadly aimed to further explore the hierarchy of adaptivity which is implied in the EffortAccuracy framework (E-Af, Payne *et al.*, 1993). This was achieved through examining the effects of increased decision complexity on information acquisition underlying decision making in a population with enhanced cognitive resources (operationalised by expertise). The results of this study demonstrate that as decision complexity, and thus task demand, increased medical experts demonstrated cognitive economy in terms of decreasing the relative amount of information processed, on both absolute and relative measures. Specifically, they spent proportionally less time on each decision, and made proportionally fewer information acquisitions during the decision under high complexity. In addition, they spent less time considering each acquisition, and became proportionally more selective in terms of acquiring information about their subjectively most important attribute. This is consistent with the broad predictions of the E-Af (Payne *et al.*, 1993), that an increase in task demand in relation to a finite amount of resources will result in the adoption of cognitively-economical, non-compensatory decision strategies.

This study also aimed to explore the effect of levels of expertise on the information acquisition process underlying decision making. The results of this study do not provide evidence that different levels of expertise result in different processing strategies under conditions of increasing complexity. Both the novice and expert groups demonstrated cognitive economy as complexity increased, in terms of the amount of information processed. In the face of increased complexity, both groups demonstrated a proportional reduction in the amount of time spent on the decision and a proportional decrease in the number of acquisitions made. Both groups spent less time on each acquisition, and demonstrated equivalent amount of time in their subjectively most important attributes. As discussed in the introduction to this chapter, there is considerable evidence that expertise leads to enhanced cognitive resources, in the sense that working memory capacity is either expanded or able to be used more efficiently. In this case, the E-Af (Payne *et al.*, 1993) would predict that on a particular decision task, the experts would demonstrate more compensatory, less economical strategies, compared to non-experts as they would not experience the same degree of cognitive strain as those with fewer resources. Thus, arguably these results are not consistent with the predictions of the E-Af, as experts adopted the same trend to cognitive economy as the novices (a decline in the amount of information processed) where the E-Af would predict that experts would not shift to cognitive economy to the same extent under an equivalent level of demand.

Given the strength of research outlining enhanced cognition in experts, it is possible that the experts did not experience the same degree of cognitive strain in the high complexity condition, and simply applied a habitual, non-compensatory decision strategy to the task. Thus, while both novice and expert groups demonstrated the use of similar decision strategies, it may have occurred for different reasons. It must be noted that this too is inconsistent with the predictions of the E-Af, which assumes that decision makers will always try to optimise the balance between decision accuracy and the cognitive cost of a particular strategy. However, if it were the case that experts were so bound by habit that they were insensitive to the precise balance between demand and resources, it would be expected that they would also apply these habitual strategies in the low complexity condition. As the results of this study clearly indicate a shift in processing strategies between low and high complexity conditions, this is evidently not the case.

Thus, it is more likely that part of expertise is the knowledge of when to employ habitual strategies that ensure relative accuracy and cognitive economy. In a medical, and particularly in an A&E environment which offers many competing demands on cognitive resources at all times, it is not difficult to see that these medical experts are likely to constantly be striving for cognitive economy while maintaining a certain level of accuracy. As such, they may come to rely on habitual, effective strategies whenever they feel even mild cognitive strain. However, before firm conclusions about the use of habitual strategies by experts can be determined, research would need to examine the information acquisition process in experts across a range of different decisions, of differing levels of demand, in a naturalistic environment. Research must be conducted on realistic tasks, as task format is important for the execution of expertise (Vicente, 1992; Vicente & Wang, 1998). This study merely served as a first step in exploring the information acquisition process underlying decision making in experts.

Interestingly, despite working in an environment that demands cognitive economy, it has been suggested that, in the domain of medical expertise, using non-compensatory strategies is regarded negatively (Hoffrage, Kurzenhauser, & Gigerenzer, 2005), as it implies that due care and attention have not been paid to patients. As such, medical practitioners cannot admit to employing such cognitively economical strategies (Hoffrage *et al.*, 2005). This attitude, in combination with the dearth of research that has been conducted on the underlying processing of medical decisions, may be detrimental to the field of medicine as a whole. Understanding the information acquisition process underlying medical decision making not only serves to educate about medical decision making (and thus abolish any prejudicial notions relating to non-compensatory strategies), but it could also play an important role in the development of medical artificial intelligence systems (Hassebrock & Prietula, 1992). The development of effective and efficient medical artificial intelligence systems could alleviate demands on doctors, freeing them from making the more simple diagnoses to enable them to spend more time on difficult cases, or even research. Thus, a good understanding of information processing underlying medical decisions is critical for the future of the field.

Chapter 9.

Study 8: Examining the effects of increased decision difficulty on the information acquisition process underlying decision making in a population with enhanced cognitive resources

9.0 Introduction

The study reported in the previous chapter was a replication of Study 4, Chapter 5, with a population with enhanced cognitive resources. Specifically, the previous study explored the effects of increased task demand through increased decision complexity on the information acquisition process in a population with enhanced cognitive resources. The study reported in this chapter will examine the effects of increased task demand through the demand source of increased task difficulty, operationalised by time pressure, on the information acquisition process in the same population. In addition, this study will continue to examine demand source differences between complexity and difficulty that have been explored in Chapters 3, 5, and 7. Broadly, this study continues the exploration into the concept of a hierarchy of adaptivity, where subtle changes in the balance between task demand and computational availability result in changes in information acquisition.

The Effort-Accuracy framework (E-Af; Payne, Bettman, & Johnson, 1993) proposes that as task demand increases, decision makers adopt increasingly cognitively-economical processing strategies in an effort to conserve their limited cognitive resources. Theories of decision making under time pressure suggest that this cognitive economy may take three forms: first, acceleration, where the decision maker spends less time on each acquisition but processes the same proportion of information in the decision space (Ben-Zur & Breznitz, 1981). Second, the decision maker may adopt filtration, where there is an increase in selectivity of information processing (Miller, 1960). Third, decision makers may shift to using non-compensatory decision strategies, which may include but are more comprehensive than the mechanisms described above (Payne *et al.*, 1993). Non-compensatory strategies vary in their cognitive cost, and range on a continuum of economy. At any point on this continuum, cost is defined by varying degrees of three factors: the amount of information processed, the selectivity of processing, and processing pattern.

As outlined in the previous chapter, expertise relates to enhanced working memory, either by minimising the number of items it needs to manipulate (Liu, Shallert, & Carroll, 2004; Tanaka, Michimata, Kaminaga, Honda, & Sadato, 2002; Yekovich, Walker, Ogle, & Thompson, 1990) or by an actual growth in capacity (Takagi, 1997). According to the E-Af (Payne *et al*., 1993), a population with greater resources should maintain more compensatory strategies in the face of rising task demand than a population with fewer resources. However, the E-Af also predicts that the experts should start to feel mild strain under the high time pressure condition, and should begin to exhibit cognitive economy. Thus, in relation to this study, the E-Af framework would predict that, in comparison to the novice population in Study 6, Chapter 7, the expert population will exhibit less cognitive economy in the high time pressure condition. This is supported by findings that the negative effects of stress, a product of time pressure, are reduced by higher skill and ability (Berkun, 1964; Lazarus & Erickson, 1952). In Study 6, novices demonstrated acceleration, as outlined by Ben-Zur & Breznitz (1981), and also demonstrated a decrease in the amount of information processed. Thus, it may be expected that experts process more information, or spend longer on acquisitions under time pressure, or even maintain compensatory processing.

It must be noted also that the field of medicine is one that often operates under high demands of time pressure. Particularly in an A&E environment, it is argued that an essential skill for A&E expertise is the ability to make rapid decisions about how individuals with severe and urgent complaints should be treated; it would not be an exaggeration to say rapid and correct treatment of patients is often a matter of life or death in an A&E environment. As such, it is possible that quick, non-compensatory strategies have developed to strong, habitual levels of use under even mild time pressure. If this is the case, there should be no obvious change in cognitive economy as time pressure increases. This would not be consistent with the predictions of the E-Af.

However, as suggested in the previous chapter, experts hold stronger, habitual strategies, but part of their expertise may be to employ them only under cognitive strain. As such, a trend towards cognitive economy under increased task demand, as predicted by the E-Af may still occur.

*Table 9.1 Possible outcomes and possible explanations when shifting from a low to a high difficulty decision task (items with a * are consistent with the predictions of the E-Af, Payne et al., 1993)*

Possible outcomes	Possible explanations
1. Compensatory decision strategies	1a. Sufficient cognitive resources to cover task demand*
2. Non-compensatory strategies	2a. Shifts in knowledge structures change information processing
	2b. Insufficient resources, shift to cognitive economy*
	2c. Sufficient resources but force of habit
3. Cognitive overload	3a. Adaptivity failure: cognitive system cannot conduct any organised search*
	3b. Habitual strategy usage leads to inappropriate strategy selection

9.1 Method

9.1.1. Participants: The participants in this study were the same 12 Accident and Emergency (A&E) consultants who participated in Study 7, Chapter 8.

9.1.2 Stimuli/ Procedure: The stimuli in this study were the same sets of decisions presented via the Mouselab software that were used in Study 6, Chapter 7. The procedure followed was identical to that of Study 6. Participants were asked to rate their subjective experience of time pressure on a scale of 1 – 3 (1 = a lot, 2 = moderate, 3 = none),

9.1.4 Dependent measures: In this study, the seven previously published measures that were used in previous studies were used: relating to amount of processing (TdTIME, ACQ, TperACQ, PTMI), selectivity (VARALT, VARATT), and pattern of search (PATTERN).

9.1.5 Analysis: The data analysis procedure followed that outlined in Study 6, Chapter 7, Section 7.1.4. In addition, to compare novice and expert decision makers, a repeated measures MANOVA of difficulty (4x4, 4x4 time pressure) and expertise level (novice, expert) was conducted on the dependent variables. A series of non-parametric tests, between and within expertise level groups, was conducted to explore any interactions.

9.2 Results

All data except VARALT and PATTERN values were log transformed due to positive skew. Co-linearity of variables was not an issue, and thus all were analysed further (see Table 9.3). Tables 9.2, 9.4 – 9.6 contain raw score descriptives, for ease of interpretation. A manipulation check for time pressure revealed that the median rating for this participant group was 2, indicating that the group felt moderate time pressure in the time pressure condition. The expert group felt significantly less time pressure in the high time pressure condition than the medical students did, $t(1,22) = -4.75, p <.001$.

9.2.1 The 4x4 condition:

As outlined in Study 7, Chapter 8.

9.2.2 The 4x4 time pressure condition: In the 4x4 time pressure condition, if every item were considered, the duration and number of acquisitions for each item would average at 2.2s and 1.3 respectively. If this is factored out in terms of alternatives, this would average out at 8.9s and 5 acquisitions per alternative. Participants spent, on average, 45% of the total decision time considering values of their subjectively most important attribute (PTMI). This was significantly longer than expected if time were distributed equally across attributes (25%), $t(11) = 14.50, p < .001$. These measures indicate a mild/moderate level of task demand in terms of the amount of information processed.

Table 9.2 Mean dependent measures by decision condition

	4x4	4x4 time pressure
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	42.60 (24.97), 16.86 – 92.25	35.50 (31.38), 9.75 – 124.42
ACQ	25 (18.0), 9 - 77	21 (15.50), 6 – 61
TperACQ (ms)	776 (305.05), 488.10 – 1518.20	745 (392.37), 304.60 – 1434.70
PTMI	.39 (.13), .24 – .71	.45 (.18), .28 – .87
	Measures of selectivity	
VARALT	.012 (.007), .001 - .022	.014 (.012), 0 - .040
VARATT	.017 (.023), .002 - .085	.028 (.040), .001 - .140
	Measure of information acquisition	
PATTERN	-.020 (.699) -.833 – .857	-.076 (.670), -1.0 – 1.0
% acquisition time	46	44

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME.

The pure measures of selectivity, VARATT and VARALT, implied a largely consistent search pattern as the variances are low (Payne *et al.*, 1988).

In terms of PATTERN, the search was neither more alternative- nor more attribute-led, compared to a consistent search value of 0, $t(11) = -0.39$, $p = .700$.

Table 9.3 Correlation matrix for dependent variables: 4x4 above the diagonal, 4x4 time pressure below.

	TdTIME	ACQ	TperACQ	PTMI	VARATT	VARALT	PATTERN
TdTIME		.81‡	.51	-.20	-.35	-.21	.23
ACQ	.79 ‡		-.01	-.23	-.32	-.23	-.01
TperACQ	.57	.29		.28	.14	.12	.42
PTMI	-.31	-.37	.25		.74 ‡	.54	-.28
VARATT	-.34	-.44	.34	.76‡		.52	-.33
VARALT	.41	.31	.69†	.48	.54		-.24
PATTERN	.09	.09	-.04	-.51	-.42	-.16	

Note. † = $p < .05$ level (2 tailed); ‡ = $p < .01$ level (2 tailed)

9.2.3 A comparison of the 4x4 and 4x4 time pressure conditions:

There were very few patterns of correlation between conditions under difficulty for the experts (see Table 9.3), unlike complexity which resulted in clear differences in search patterns as judged from the relationships between variables. Under both low and high difficulty, TdTIME was positively highly correlated with ACQ; again, this is the most consistent relationship between variables across all studies reported herein. In both conditions, VARATT was also positively correlated with PTMI, indicating that more selective searches were always associated with relatively more time spent in the subjectively most important attribute, which is a logical relationship. Additionally, in the high difficulty condition, TperACQ was positively associated with VARALT, indicating that under time pressure, search patterns that were more selective across attributes also resulted in more time being spent on each acquisition.

A repeated measures MANOVA of difficulty (4x4, 4x4 time pressure) for the transformed dependent variables (TdTIME, ACQ, TperACQ, PTMI, VARATT) and the variables VARALT and PATTERN revealed no main effect of difficulty, $F(7,5) = .62, p = .728$. However, there were significant differences of difficulty in TdTIME, $F(1, 11) = 5.49, p = .039$, and in PTMI, $F(1, 11) = 6.09$, $p = .031$. Thus, under time pressure, participants took significantly less time to make their decisions, and spent significantly more time considering their subjectively most important attribute.

No significant effects of difficulty were found for ACQ, $F(1, 11) = 2.65$, $p = .132$, TperACQ, $F(1, 11) = 1.23$, $p = .290$, VARATT, $F(1, 11) = 1.19$, $p = .299$, VARALT, $F(1, 11) = .33$, $p = .577$, and PATTERN, $F(1, 11) = .18$, $p = .680$. There was no significant deviation from normality for the residuals of any of the dependent variables. Thus, participants did not significantly change the number of acquisitions made or the speed of those acquisitions, were not more selective in their information acquisition, and did not change their search pattern to a more non-compensatory attribute-led pattern under time pressure.

The ratio of acquisition time to deliberation time was not significantly different across conditions, $t(11) = -0.23$, p = .821.

9.2.4 A comparison of the difficulty (4x4 time pressure) and complexity (8x8) conditions:

To account for decision size differences, variables relating to the amount of processing which are susceptible to decision size (TdTIME, ACQ, PTMI) for both difficulty (4x4 time pressure) and complexity (8x8) conditions were transformed into ratio values in terms of their baseline 4x4 values (see Table 9.4). A series of paired samples t-tests for these transformed values revealed significant differences in demand source

Table 9.4 Transformed ratio values for amount of processing measures

	4x4 time pressure	8x8
	Ratio measures of information processing	
	M (*SD*)	*M* (*SD*)
rTdTime (s)	.81 (.31)	2.17 (1.29)
rACQ	.89 (.37)	2.65 (1.69)
rPTMI	1.18 (.23)	.93 (.28)

Note. rTdTime = total time to decision ratio; rACQ= ratio of number of information boxes examined; rTperACQ = time per information acquisition ratio; rPTMI = ratio of proportion of time spent on subjectively most important attribute

(complexity vs. difficulty) for TdTIME, $t(11) = 3.68, p = .004$, ACQ, $t(11) = 3.95, p = .002$, and PTMI, $t(11) = -2.24, p = .047$. Thus, complexity as the demand source of increased task demand led to a significantly longer average total decision time, and a significantly greater number of acquisitions than did difficulty. In addition, complexity resulted in significantly less time spent on the subjectively most important attribute, compared to difficulty.

A repeated measures MANOVA of decision type (4x4 difficulty, 8x8 complexity) for the transformed dependent variables (TperACQ, VARATT) and VARALT and PATTERN that were not susceptible to decision size effects revealed no main effect of decision type, $F(4,8) = .37, p = .822$. There were no significant effects for decision type for TperACQ, $F(1,11) = 0.72, p = .415$, VARATT, $F(1,11) = .31$ $p = .587$, VARALT, $F(1,11) = 0.15, p = .707$, or PATTERN, $F(1,11) = 0.29, p = .600$. Participants did not differ in the amount of time per acquisition, the selectivity, or type of search pattern in the face of different demand sources.

9.2.4 A comparison of expertise levels and decision difficulty

A repeated measures MANOVA of difficulty (4x4, 4x4 time pressure) by expertise level (novice, expert) for the transformed dependent variables (TdTIME, ACQ, TperACQ, PTMI, VARATT) and the variables VARALT and PATTERN revealed a main effect of difficulty $F(7, 15) = 4.67, p = .006$. This arose through effects in TdTIME, $F(1, 21) = 16.61, p = .001$, ACQ, $F(1, 21) = 4.86, p = .039$, TperACQ, $F(1, 21) = 4.67, p = .042$, and PTMI, $F(1, 21) = 17.96, p < .001$.

There was no main effect of expertise level, $F(7, 15) = 3.28, p = .070$. Specifically, there were no effects of expertise on TdTime, $F(1, 21) = 1.12, p = .302$, ACQ, $F(1, 21) = 3.68, p = .069$, TperACQ, $F(1, 21) = .23, p = .635$, PTMI, $F(1, 21) = 2.99, p = .098$, VARATT, $F(1, 21) = .30, p = .590$, VARALT, $F(1, 21) = .53, p = .475$, and PATTERN, $F(1, 21) = .185, p = .672$.

Table 9.5 Mean dependent measures by expertise level for the 4x4 condition

	Novices	Experts
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	61.73 (43.17), 16.42 – 180.72	42.60 (24.97), 16.86 – 92.25
ACQ	38 (20.65), 13 - 87	25 (18.0), 9 – 77
TperACQ (ms)	879 (295.53), 510.40 – 1426.10	776 (305.05), 488.10 – 1518.20
PTMI	.25 (.08), .13 – .40	.39 (.13), .24 – .71
	Measures of selectivity	
VARALT	.031 (.016), .001 - .048	.012 (.007), .001 - .022
VARATT	.017 (.069), 0 - .240	.017 (.023), .002 - .085
	Measure of information acquisition	
PATTERN	.113 (410) -.739 – .684	-.020 (.699), -.833 – .857
% acquisition time	54	46

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME.

There was no overall interaction between difficulty and decision domain, $F\,(7, 15) = 1.82, p = .156$; although there was a significant interaction between expertise levels and complexity on PTMI, $F\,(1,21) = 6.95, p = .015$. Two unrelated t-tests of expertise level and difficulty were conducted on this variable to explore the interaction further. There was a significant difference between novices and experts on PTMI4, $t(22) = -3.26, p = .004$. However, there was no significant difference between novices and experts on PTMI time pressure, $t(22) = .01, p = .996$. Thus, on the no time pressure condition, it can be argued that the experts were significantly more selective in terms of their most important attribute than were the novices. As time pressure increased, both groups became significantly more selective on their most important attribute.

Table 9.6 Mean dependent measures by expertise level for the 4x4 time pressure condition

	Novices	Experts
	Measures of information processing	
	M (*SD*), range	*M* (*SD*), range
TdTime (s)	45.57 (34.01), 17.80 – 131.20	35.50 (31.38), 9.75 – 124.42
ACQ	32 (21.20), 14 - 85	21 (15.50), 6 – 61
TperACQ (ms)	702 (217.13), 396.40 – 1256.80	745 (392.37), 304.6 – 1434.70
PTMI	.46 (.18), .26 – .75	.45 (.18), .28 – .87
	Measures of selectivity	
VARALT	.008 (.006), .001 - .022	.014 (.012), 0 - .040
VARATT	.027 (.029), 0 - .089	.028 (.040), .001 - .140
	Measure of information acquisition	
PATTERN	-.001 (.444) -.526 – 1.0	-.076 (.670), -1.0– 1.0
% acquisition time	51	44

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing. % of acquisition time = the amount of total decision time spent actually acquiring information, i.e. (ACQ x TperACQ/1000)/TdTIME.

9.3 Discussion

This study aimed to explore the effects of increased task demand in the form of increased time pressure on the information acquisition process underlying decision making in a population with enhanced cognitive resources. The Effort-Accuracy framework (E-Af, Payne *et al.*, 1993) proposes that as task demand increases, decision makers are more likely to adopt cognitively-economical strategies in the face of finite cognitive resources. The results of this study suggest that as task demand (operationalised by complexity) increased, the medical experts demonstrated cognitive economy in terms of the amount of information processed. Specifically, as time pressure increased, the experts took significantly less time to make their decision, and spent significantly more time considering attribute information from their subjectively most important attribute. This is consistent with the broad predictions of the E-Af.

The theories of time pressure decision making include acceleration (Ben-Zur & Breznitz, 1981), filtration (Miller, 1960), and comprehensive decision strategy shifts (Payne *et al.*, 1993). The results of this study do not provide support either for acceleration or filtration, as the average time spent on acquisitions did not change in the face of time pressure, and the experts did not become more selective across attributes or alternatives. However, the results are consistent with a shift in decision strategy, as suggested by Payne *et al.*, as the experts did demonstrate a decrease in the amount of processing. The E-Af framework implies that non-compensatory strategies vary in the degree of cognitive economy they represent (Payne, Bettman, & Luce, 1996). The results reported here would be consistent with a shift to a first-stage non-compensatory strategy, in the face of mild cognitive strain. Only in the face of more severe cognitive strain would selectivity and/or a shift in processing pattern be adopted.

The E-Af (Payne *et al.*, 1993) also proposes that the decision strategy employed by a decision maker on a particular task is the result of the precise balance between task demand and the cognitive resources of the decision maker. The ability to determine the precise balance between task demand and resources, and the resulting selection of the appropriate decision strategy to maximise accuracy and minimise cognitive cost, has been termed in this thesis the 'hierarchy of adaptivity.' This study aimed to explore this hierarchy of adaptivity, in comparing information acquisition on a particular decision task of a consistent level of demand between a group with normal cognitive resources and one with enhanced resources. Both the novice group in Study 6, Chapter 7 and the expert group used in this study demonstrated some degree of cognitive economy in the face of increased time pressure. However, the novices demonstrated a greater reduction in the amount of information processed (and thus greater cognitive economy) than the experts. While both groups demonstrated a decrease in decision time and an increase in the amount of time spent on their subjectively most important attribute, the novices also arguably accelerated their acquisitions. In terms of the theories of time pressure, novices showed evidence for acceleration of processing, while the experts did not. The experts did spend a greater amount of time in their subjectively most important attribute than the novices did in the low time pressure condition, which suggests some cognitive streamlining when task demands did not outweigh resources. However, arguably, this is very mild cognitive economy, and this difference disappeared in the high time pressure condition. Overall, these results are not inconsistent with the E-Af, in the sense that the group with greater resources did not adopt such severe cognitive economy in the face of equivalent demand. These results also provide interesting insights into the process of expert decision making in terms of information acquisition in the face of changing task demands. Expertise appeared to lead to enhanced resources, in that they used more cognitively-effortful strategies for in the face of rising task demand.

The results of this study also provide some insight into the importance of considering demand source: the relative demand of tasks rooted in increased difficulty versus those rooted in increased decision complexity. In the novice medical participants, both complexity and difficulty led to the same cognitive response; a reduction in the amount of information processed. Specifically, both demand sources under conditions of high demand resulted in reduced decision times, more rapid acquisitions, and an increase in the selectivity of processing of the subjectively most important attribute. However, in the expert population, there were demand source differences. For the medical experts, decision complexity appeared to demand more cognitive effort, as difficulty ratios were nearer to baseline values. In terms of overall response, complexity appeared to lead to greater cognitive economy than did decision difficulty.

As outlined in the introduction, it is possible that non-compensatory strategies become habitual for medical experts, in the face of constant time pressure. Certainly, the rating of subjective time pressure for the experts was only moderate, while novices felt high levels of time pressure. This suggests a certain habituation to time pressure. It may be argued the lower time pressure ratings reflected a lack of motivation on the part of the experts for this task, but it could also be that the experts had more to prove in terms of their expertise and thus motivation was not an issue. However, as there is some evidence of adaptivity in terms of decision time and amount of time spent on the subjectively most important attribute, it is unlikely that experts employed habitual strategies equally across decision conditions. Habitual strategy usage implies employing the same strategy in a variety of situations, sometimes maladaptively. It does not generally imply flexibility or adaptivity within or across strategies. Habitual strategy usage, and the flexibility of habitual strategies, is an area that is vastly under-researched, and as mentioned in Chapter 8, Section 8.3, should be studied further in expert populations. It is possible that, in a naturalistic environment, habitual strategy usage is stronger. Thus, it is suggested that, in light of current knowledge in the field, the results reported here support the concept of a hierarchy of adaptivity, within the E-Af, as different balances between cognitive resources and task demand result in different decision strategies.

Chapter 10.

General discussion

10.0 Overview

This thesis reports a research program that examined the concept of a hierarchy of adaptivity. This hierarchy is implicit in the Effort-Accuracy framework (E-Af; Payne, Bettman, & Johnson, 2003). The E-Af is a cost-benefit, descriptive framework of decision making, which assumes that the information acquisition process underlying decision making can be viewed in terms of common decision strategies, which range from cognitively-effortful, compensatory strategies to more cognitively-economical, non-compensatory ones. The E-Af proposes that these different decision strategies, despite incurring differing cognitive costs, are associated with different degrees of accuracy. The cognitive cost of a strategy is primarily determined by three main components: the amount of information processed, the selectivity of processing, and the pattern of search. The selection and implementation of a decision strategy is a result of the precise balance between task demand, or the computational load of the decision, and the amount of cognitive resources the decision maker has available for that task.

A hierarchy of adaptivity in terms of decision strategy selection is not explicitly stated in the E-Af (Payne *et al.*, 1993), although it is implied in its description. The E-Af states that, at different points along the continuum of task demand, different decision strategies will be adopted to maximise decision accuracy. As the decision maker's cognitive resources become increasingly taxed, they adopt increasingly cognitively-economical strategies. This progressive adaptation to an increasing mismatch between demands and resources represents a hierarchy of adaptivity. A hierarchy of decision strategies is defined by the amount of effort they demand: along the continuum, strategies range from highly, cognitively effortful, compensatory strategies, to cognitively economical, non-compensatory strategies (Payne *et al.*, 1993). However, to date the assumption has been that this hierarchy is represented through broad shifts in decision strategies, rather than gradual, subtle shifts within strategy types. In addition, as far as can be ascertained, no research program has examined this hierarchy through a consistent manipulation of the balance between task demands and computational availability.

The studies reported in this thesis represent manipulations of the balance between task demands and the cognitive resources of the decision maker. This thesis recruited young adults to represent a cognitively optimal population, older adults to represent a population with diminished cognitive resources, and medical experts to represent those with enhanced cognitive resources. Thus, the amount of cognitive resources available for the task was manipulated, quasi-experimentally, through different populations of decision makers. Each of these participant groups was asked to make decisions under both low, and high, task demand. Increased task demand was operationalised either by increased decision complexity or by increased decision difficulty. Increased complexity was manipulated by increasing the size of the decision space by 4, from 16 pieces to 64 pieces of information available in the space. Increased difficulty was manipulated with time pressure. Thus, a low demand decision was always one of no time pressure, involving 16 items of information, while high demand decisions were defined as those involving 64 items of information and no time pressure, or 16 items of information and time pressure. The effects of increased task demands, through both complexity and difficulty, were measured in terms of the information acquisition process underlying decision making. Specifically, the effects of increased task demands were examined in terms of the amount of information processed by the decision maker, the selectivity with which information was processed, and the pattern of search of the information in the decision space.

This research program enabled conclusions to be drawn about this broad investigation into the hierarchy of adaptivity, but also offered additional insights into decision making and ageing, decision making and expertise, the effect of different decision domains on information acquisition, and the effect of the demand source of the increased task demand on the underlying decision making process. A search of the literature revealed no studies that have explored the effects of increased task demand on the information acquisition process underlying decision making in both ageing and expert populations. Furthermore, no studies were found which have highlighted the importance of decision domain differences on the information acquisition process underlying decision making, or the importance of considering demand source in determining task demand. Notably, this

Table 10.1 Summary of study outcomes

Population	Demand source	Result
Younger adults	Decision complexity	Increased cognitive economy: decline in the relative amount of information processed (TdTIME and ACQ)
Younger adults	Decision difficulty	Increased cognitive economy, decline in the amount of information processed (TdTIME, ACQ and TperACQ)
Older adults	Decision complexity	Increased cognitive economy, decline in the relative amount of information processed (TdTIME, ACQ) and shift to attribute-led search pattern
Older adults	Decision difficulty	Increased cognitive economy, decline in the amount of information processed (TdTIME, ACQ, PTMI*) and increased selectivity across attributes
Novices	Decision complexity	Increased cognitive economy, decline in the relative and absolute amount of information processed (TdTIME, ACQ, TperACQ, PTMI)
Novices	Decision difficulty	Increased cognitive economy, decline in the amount of information processed (TdTIME, PTMI, TperACQ*)
Experts	Decision complexity	Increased cognitive economy, decline in the amount of information processed (TdTIME, ACQ, TperACQ, PTMI)
Experts	Decision difficulty	Increased cognitive economy, decline in the amount of information processed (TdTIME, PTMI)

Note. TdTime = total time to decision; ACQ= number of information boxes examined; TperACQ = time per information acquisition; PTMI = proportion of time spent on subjectively most important attribute; VAR-ALT = variance in the proportion of time spent on each alternative; VAR-ATT = proportion of time spent on each attribute; PATTERN = index reflecting relative amount of attribute-led (-) vs. alternative led (+) processing.

* trend towards significance

thesis revealed that shifts towards cognitive economy may be more subtle than previously accounted for in the literature, and increases in cognitive economy can be judged by changes within each of the 3 broad factors that relate to the demand of decision strategies (amount of processing, selectivity of search, pattern of search). A summary of the findings of the studies reported in this thesis can be found in Table 10.1.

10. 1 Decision making in a young adult population

Chapters 2 and 3 of this thesis explored the information acquisition process in a young adult population, in the face of increased task demand by both increased complexity and difficulty.

Previous research in this area and on this age group has reported results that are consistent with the E-Af: participants adopt more cognitively economical decision strategies as demand increases (Biggs, Bedard, Gaber, & Linsmeier, 1985; Billings & Marcus, 1983; Grether, Schwartz, & Wilde, 1985; Grether & Wilde, 1983; Klayman, 1985; Onken, Hastie, & Revelle, 1985; Payne, 1982; Payne, Bettman, & Johnson, 1988; Payne & Braunstein, 1978; Shields, 1980; Sundstrom, 1987).

However, as outlined in Chapter 2, the studies listed above employed a range of decisions in different domains, with varying levels of structural complexity. They also did not examine the effects of the source, or reason behind, increased task demand. The studies presented herein attempted to minimize the effects of any confounding variables in decision structure by keeping the decision space as clean (i.e. free from confounding variables) as possible. In addition, the studies in this thesis studied the effects of two different types of demand source (increased complexity and increased difficulty).

The results of the studies in this thesis provide support for the predictions of the E-Af (Payne *et al.*, 1993), although to a lesser degree than previous studies listed above. Young adults adopted increasing cognitive economy in the face of both increased task complexity and task difficulty. Specifically, in the face of increased complexity, participants reduced the amount of information they processed: they spent proportionately less time making their decisions and made fewer acquisitions.

Participants also reduced the amount of information they processed in response to increased task difficulty. As in response to complexity, they spent less time on their decisions and made fewer acquisitions; however they also demonstrated acceleration of processing in terms of a reduction on the amount of time spent per acquisition (Ben Zur & Breznitz, 1981). Thus, in the face of increased task demand from varying sources, participants demonstrated increased cognitive economy as predicted by the E-Af.

As mentioned, the shift to different decision strategies was not as clear as reported in past research: participants did not become more selective, nor change the pattern of their search. As outlined in Chapter 2, this is thought to be the result of a more pure decision space, which represented a lower level of demand than those used in other studies. A lower level of demand resulting in a lesser degree of cognitive streamlining is precisely what the E-Af (Payne *et al.*, 1993) would predict.

10.2 Decision making and ageing

Chapters 4 and 5 of this thesis explored older adults' decision making. This is an area that is critically under-researched (Peters, Finucane, MacGregor, & Slovic, 2000), especially in terms of information acquisition changes in response to changes in task demands. As outlined in Chapter 4, Section 4.0, there are a variety of cognitive changes associated with the ageing process (Bäckman, Small, Wahlin, & Larsson, 1999; Craik, 1977; Craik & Jennings, 1992; Craik & McDowd, 1987; Holtzer, Stern, & Rakitin, 2004; Maciokas & Crognale, 2003; Schaie & Willis, 1996; Park & Shaw, 1992; Rogers, 2000; Zacks & Hasher, 1997). Of particular interest to decision making are changes in attention and working memory (Craik & Byrd, 1982; Light, 2000; Verhaeghen, Marcoen, & Goossens, 1993), which represent an age-related decline in cognitive resources (Charness, 1985; Craik, 1986; Craik & Salthouse, 2000; Park & Schwartz, 2000; Reese & Rodeheaver, 1985).

Research into older adults' decision making, which used a self-report paradigm, suggests that they adopt more cognitive-streamlining than younger adults (Klaczynski &

Robinson, 2000), and adopt more non-compensatory strategies (Johnson, 1990). Specifically, older adults relied more on heuristic, automatic processing with age (Park, 1999). In terms of information acquisition, older adults have been found to engage in more efficient searches in that they recheck decision information less frequently (Johnson, 1990). In addition, older adults have been found to be more selective in the type of information they process (Meyer, Russo, & Talbot, 1995; Riggle & Johnson, 1996; Walsh & Hershey, 1993; Zwahr, Park, & Shifren, 1999), but to take longer to consider this information and reach a decision (Johnson, 1990; Johnson, Schmitt, & Pietrukowicz, 1989; Riggle & Johnson, 1996).

The investigation into older adult decision making in this thesis represents an improvement on the research reported above, in that it follows a process tracing methodology. In a self-report paradigm, the data obtained is limited to that which the participant feels merits communication. It also assumes that participants are aware of each step in their information acquisition process. A computer-based process tracing system enables accurate recording of all steps in the information acquisition process. Thus, it ensures more accurate, objective data. In addition, this is the first work to consider the effects of different types of demand source underlying task demand on older adults' decision making.

The results of these studies support previous findings of an age-related shift towards greater cognitive economy. In response to increased decision complexity, compared to younger adults, older adults generally took more time to acquire information, spent more time on their most important attribute, and were more selective in their searches, across both attributes and alternatives. This is consistent with previous findings (Johnson, 1990; Johnson *et al.*, 1989; Meyer *et al.,* 1995; Riggle & Johnson, 1996; Walsh & Hershey, 1993; Zwahr *et al.,* 1999). In addition, consistent with Johnson (1990), older adults were more attribute-driven in their search than younger adults, in the low complexity condition. Older adults adopted more attribute-led patterns of search as complexity increased, and younger adults shifted to become more attribute-led in their search patterns. A shift to a more attribute-led search pattern is indicative of non-compensatory strategies (Payne *et al.,* 1993). In addition, while both young and older adults demonstrated an increase in the time spent in the subjectively most important attributes, older adults spent more time on this attribute under high complexity than did younger adults. These results indicate that older adults were adopting non-compensatory strategies even under the low complexity condition. Regardless of complexity, older adults not only processed less information than younger adults, they also took longer to do so. Again, this is consistent with previous research (Johnson, 1990; Johnson *et al.,* 1989; Riggle & Johnson, 1996). Thus, the studies reported here demonstrate that older adults were more cognitively-economical than younger adults in the face of both high and low complexity conditions.

An increase in task difficulty also led to cognitive streamlining. Generally under task difficulty, compared to younger adults, older adults made fewer acquisitions, spent more time on each acquisition, spent more time on their subjectively most important attribute, and were more selective across attributes and alternatives than younger adults. This, too, is consistent with previous findings (Johnson, 1990; Johnson *et al.*, 1989; Riggle & Johnson, 1996; Walsh & Hershey, 1993; Zwahr *et al.*, 1999). Older adults did not demonstrate any acceleration of processing, as younger adults did, and they were also more selective across attributes than younger adults in the face of both low and high task difficulty. While high time pressure did not affect selectivity in younger adults, it caused older adults to become significantly more selective across attributes. Also, older adults spent more time on their subjectively most important attribute under time pressure.

Thus, these results indicate that increases in task demand, regardless of demand source, led to increased cognitive economy in an older adult population, compared to a younger adult population. It is interesting that the different demand sources led to slightly different types of cognitive streamlining, particularly in terms of pattern of search and selectivity. Older adults were more selective across attributes under high task difficulty, and spent more time in their subjectively most important attribute under high task complexity. This thesis proposes that this differential response to demand source demonstrates adaptivity in older age, which suggests that older adults are not simply applying automatic, habitual strategies to an overall increase in task demand.

10.3 Decision making and expertise

Chapters 8 and 9 of this thesis explored the effects of expertise on decision making, an area that has been under-researched in terms of information acquisition and decision strategies. Expertise is defined as an exceptional competence relying on internal knowledge structures (Hakkarainen, 2002), and is characterised by increased domain-specific declarative knowledge (Yekovich, Walker, Ogle, & Thompson, 1990). As outlined in Chapter 8, Section 8.0, expertise may be considered to represent enhanced cognitive resources, either in terms of enhanced working memory capabilities through increased efficiency (Yekovich *et al.*, 1990), or in terms of an actual expansion of working memory capacity (Tagaki, 1997). With regard to the former, it has been suggested that this enhancement of working memory is due to domain-specific knowledge rendering working memory more efficient. Specifically, expertise has been shown to lead to increased selectivity of information entering working memory, the ability to form larger chunks of information (Liu, Schallert, & Carroll, 2004), or outsourcing cognitive activity to other areas of the brain (Tanaka, Michimatc, Kaminaga, Honda, & Sadato, 2002).

As outlined above, and in Chapter 8, very little research has explored the effects of expertise on the information acquisition process underlying decision making, and what findings have been reported are mixed. Outside of the medical decision domain, it was suggested that experts do not search information in the decision space differently to novices, but make better quality decisions with that information (Patrick, 1996). However, research using a naturalistic methodology (i.e. studying experts in their professional environment) shows that experts employ more non-compensatory strategies than novices: specifically, they take less time to make the decision, make fewer acquisitions, and search a different amount of information (Klein & Brezovic, 1986; Salterio, 1996). By contrast, within the medical domain it has been reported that medical experts are more likely to employ non-compensatory, 'fast and frugal' strategies than novices (Hoffrage, Kurzenhasuer, & Gigerenzer, 2005), and only use a small amount of information in the decision space to make their decisions (Dhami & Harries, 2001).

According to the E-Af, enhanced cognitive resources, such as those represented by expertise, will delay the shift to non-compensatory strategies, compared to the effect of fewer cognitive resources and equivalent task demand. Thus, it would be expected that with high task demand, experts would demonstrate less cognitive economy than novices. However, it was also suggested that expertise may lead to the employment of more established, habitual decision strategies, as a result of experience. It is also possible that expertise leads to qualitative changes in information processing, not quantitative changes. For example, experts may process the same amount of information in a decision space, but process it in different ways. Their knowledge would guide the process in particular ways, which may not be evident simply in terms of the amount of information processed, or the selectivity or pattern of search of this information. Thus, established, domain-specific knowledge may lead to information being considered differently, but not necessarily alter how it is acquired.

The results of the studies in this thesis provide some evidence for expertise differences in information acquisition. While statistically significant expertise differences were not always found, they are indicated, nonetheless, in a direct comparison of responses to increased demand. In the face of increased task complexity, there was no statistically significant difference in information acquisition between the novice and expert groups. Both groups demonstrated cognitive economy as complexity increased, in terms of the amount of information processed. However, a comparison of each group's response to increased complexity suggests that the experts engaged in arguably more cognitive streamlining under high complexity. This is not consistent with the predictions of the E-Af.

In terms of increased task difficulty, expertise effects emerged in statistical analysis in that, as task difficulty increased, experts did not accelerate their processing, while novices did. This indicates that experts were engaging in more cognitively effortful processing. In addition, the medical experts spent more time acquiring information from their subjectively most important attribute; however this effect was not evident under high task difficulty. Under low task difficulty, the experts were significantly more selective in terms of their most important attribute than were the novices. However, as task difficulty increased, both groups became significantly more selective on their subjectively most important attribute. The novices became so much more selective that differences between expertise levels disappeared, and the experts were no more selective than the novices.

Thus, under increased task demands, either from complexity or difficulty, no conclusive evidence that experts processed information differently from novices was found. The only significant difference was that experts engaged in less cognitive-streamlining under high task difficulty, and arguably slightly more under high task complexity, although this was not borne out by statistical analysis across groups and conditions. These results are not consistent with those of Hoffrage *et al.* (2005), Klein and Brezovic (1986) or Salterio (1996). However, they may be consistent with those of Patrick (1996), although as decision quality was not considered, this cannot be determined. It is possible that the studies reported in this thesis were unable accurately to measure domain-specific expertise in an artificial setting. It is clear, however, that further research into the effects of expertise and decision making should be conducted, in a program where both information acquisition and decision quality are considered and, perhaps, in a naturalistic setting.

10.4 Ageing vs. Expertise

While the results of the ageing studies could not directly be compared with those from the expertise studies due to decision domain differences, the different effects of diminished cognitive resources and enhanced cognitive resources on the information acquisition process can be discussed.

As outlined in Chapter 4, Section 4.3, some researchers have suggested that ageing represents expertise, as older adults have had more life experience and are thus 'experts in life' (Poon & Siegler, 1991; Tagaki, 1997; Viggiano, Righi, & Galli, 2005). However, it was argued in Chapter 4 that ageing and expertise represent distinct cognitive changes. As outlined above, expertise is characterised by increased domain-specific, declarative knowledge (Yekovich *et al.*, 1990). Domain-specific knowledge has been found to be impervious to age effects (see Ericsson & Lehman, 1996; Masunaga & Horn, 2001), and training on a task does not mediate age effects (Meinz & Salthouse, 1998), which suggests they are distinct. Patrick (1996) argues that age and expertise are not synonymous, and must be considered separately. In addition, the decision task undertaken by older adults in this thesis was designed to be relatively free of domain-specific experience.

A comparison of the effects of ageing and expertise on information acquisition supports the notion that they are separate cognitive factors. Ageing and expertise resulted in very different responses in information acquisition, compared to their respective comparison populations. Generally, as task demand increased, regardless of demand source, older adults exhibited a greater degree of cognitive economy than did experts. Not only did they demonstrate a reduction in the amount of information processed, older adults also demonstrated increased selectivity across attributes and alternatives, and a more attribute-led search. These are indicative of the use of non-compensatory strategies (Payne *et al.*, 1993). Conversely, experts did not demonstrate more cognitively-economical strategies in the face of increasing task demand, compared to novices. In fact, they engaged in more cognitively-effortful processing in the face of high task difficulty. Thus, this differential response of experts and older adults indicates that expertise and ageing are, indeed, different cognitive factors.

10.5 Decision domain differences

Research in decision making, and particularly that focusing on the processes underlying decision making, has failed to recognise that decision domain, or the topic of decision, may influence the information acquisition process. As far as can be ascertained, this research program is the first to examine the effects of decision domain on information acquisition. The topics used in this study were a holiday domain (selecting a hotel for a holiday, Chapters 2 and 3) and a medical domain (selecting which patient from a group should be seen first, Chapters 6 and 7). Decisions of equal computational demand in terms of complexity (number of attributes and alternatives) and difficulty (time pressure or no time pressure) were presented to two age-equivalent groups, and the responses to these factors were compared across domains.

The studies reported in this thesis indicate that decision domain affects the information acquisition process. While both domain groups became more cognitively-economical under increased demand, different domains resulted in different responses following increases in task demand, whether from increased task complexity and/or difficulty. In terms of increased task complexity, the different decision domains resulted in differences in the amount of information processed. The medical domain group spent longer on each acquisition regardless of complexity level, and they reduced their acquisition time significantly under high complexity. The holiday domain group spent less time on acquisitions than the medical domain group, and did not reduce their average acquisition times as complexity increased. In addition, as complexity increased, the medical domain group spent more time on their subjectively most important attribute, while the holiday domain group became less selective under high task complexity.

The holiday and medical domain groups also responded differently to increased task difficulty. When decision difficulty was low, the domain groups were no more selective in terms of their most important attribute (PTMI); however, in the high task difficulty condition, the medical domain participants spent significantly longer in their subjectively most important attribute. Thus, in the face of increasing time pressure, participants in the medical decision domain become increasingly selective, while the holiday decision domain group did not. In addition, while the holiday decision domain group significantly accelerated their processing under time pressure, the evidence for acceleration in the medical decision domain group was not as strong. Decision domain differences can also be seen in differential responses to demand source between groups. The holiday domain group had a different response to complexity than they did to difficulty; while both demand sources led to a reduction in decision time and the number of acquisitions made, difficulty also led to acceleration of processing. However, the medical decision domain group demonstrated the same response regardless of demand source: both complexity and difficulty led to reduced decision times, fewer and more rapid acquisitions and an increase in the selectivity of processing on the subjectively most important attribute.

The studies reported in this thesis do not represent an exhaustive investigation into decision domain effects. Certain constraints to their evaluation must be noted: first, that sample sizes differences exist between the medical and hotel decision making groups. While the number of participants in the medical group does not represent a small number of participants for this type of study, given the number of data points produced per participant, it would be advisable to conduct further work on equivalently-sized participant populations. Second, the presentation of information was not completely equivalent across domains: while every attempt was made to present the medical information numerically, it was impossible to do so. Every attempt was made, and the medical expert consulted, to present verbal information as concisely as possible, to minimise demand. However, it is acknowledged that the difference in the presentation of information renders the direct comparison of this data more problematical. More importantly, domain effects were compared between two different groups of decision makers. As such, it is acknowledged that these results may not reflect true decision domain differences, but might result from differences in decision making strategies between populations. It is possible that certain personality traits that led some students to select medicine as a subject may be associated with styles of decision making. In addition, it is interesting to consider the effects of outcome (i.e. the severity of consequences of the decision made) in each of the domains on the decision strategies that may be employed. For example, those in the medical field are trained to avoid false negatives (i.e. Type 2 errors), and this is not reflected equivalently in the domain on choosing hotels for a holiday. It is possible that the domain effects seen here are due to such inherent different values in outcomes. In addition, it is possible that the way in which the decision information was presented in these studies was more representative of information in a holiday domain; in other words, it is possible that a matrix-style representation of information is more artificial in a medical domain, and that this may be influenced the resulting decision strategies. The RPD model of decision making claims that experts that experts integrate information to create a more holistic, intuitive response (Klein et al., 1986), and the delineated 'attribute per alternative' style of representation may not facilitate expert decision making. A more comprehensive research program in this area could focus on one population, and examine the changing information acquisition process across a variety of domains within that group. Ideally, studies should employ a population which has some decision-specific knowledge in two or more areas, and employ identical decision matrices in terms of structure and attribute values. An ideal population for this type of study would be those with both professional and other expertise, such as a medical doctor who is also an expert in chess, or one who is a motor enthusiast.

10.6 The effects of demand source on the information acquisition process

The aim of this thesis was not to directly compare the effects of demand source on the information acquisition process, but rather, to use different demand sources as examples to illustrate change across a continuum of adaptivity. However, the results of the studies in this thesis do provide some insight into the possible influences of the demand source, i.e. the cause of increased task demand, on the decision making process, though a preliminary comparison of difficulty and complexity data within each population group. These studies operationalised increases in task demand through two different mechanisms: task complexity and task difficulty, both of which relate to objective, rather than subjective, levels of task demand. As outlined in the introduction, it is argued that decision complexity is linked to structural features of the decision itself, whereas decision difficulty is determined by internal and external factors. In terms of past research and, according to the E-Af (Payne *et al.*, 1993), task demand has been viewed as a unitary measure of cognitive load along a single continuum. The level or degree of demand could increase or decrease along this continuum, as difficulty or complexity increased, resulting in the selection of different decision strategies according to the point on the continuum.

The results of this research program provide some insight into the importance of including demand source in the determination of task demand, a factor that has previously been overlooked. Demand source effects can be seen across all groups, as well as within them. According to the E-Af (Payne *et al.*, 1993), decision makers will engage in the most effortful processing they can, within their limitations, and will only adopt cognitive economy when demand necessitates it. In these studies, for all groups, decision complexity appeared to result in a greater amount of processing than decision difficulty when the conditions were compared directly, using ratio values for amount of processing variables. Generally, decision complexity resulted in longer decision times and more acquisitions made, compared to the baseline (4x4) values. For all of the groups, except the novice medical students, complexity also resulted in less time spent on the subjectively most important attribute, i.e. time more evenly distributed across all attributes.

However, when the results of the studies are compared at face value (e.g. in Table 10.1), it appears that decision complexity leads to more severe cognitive streamlining than decision difficulty. Within groups, demand source differences are evident in terms of the differential response in information acquisition patterns. In terms of the holiday student population, difficulty resulted in acceleration of processing, as well as a reduction in both decision time and number of acquisitions. The medical student population also responded differently to demand sources; complexity led to a decrease in acquisitions, while acquisitions in the difficulty condition were fewer, but consistent in number across conditions. In the cognitively-diminished population, both complexity and difficulty resulted in shorter decision times and fewer acquisitions; however, complexity led to a more attribute-led search, while difficulty led to more selectivity of processing across attributes and alternatives. In a cognitively-enhanced population, both complexity and difficulty resulted in shorter decision times. However, complexity led to a reduction in the number of acquisitions made, while difficulty did not.

However, it is strongly noted that no definitive conclusions can be drawn here about the relative effect of demand source. While decision source differences are clear, in that the responses of the participants to different decision sources varied, it is difficult to compare relative effects to determine the direction of this difference, as decision size effects confound the picture.

In addition, the issue of the potential difficulty in measuring the separate effects of decision source, due to the overlap between decision complexity and decision difficulty in any given decision, must be considered. At any point, decision complexity (as defined by the decision) and decision difficulty (relating to internal and external factors to the decision maker) combined result in an objective level of task demand. Thus, strictly speaking, in all conditions, decision complexity and difficulty as variables are present and cannot be separated.

The main focus of this thesis was to examine the adaptivity of decision making to increases in task demand; the source of which was explored to elaborate on the body of knowledge about adaptivity. Given the predominant framework in the field of adaptivity presents a framework based on resources available to represent effort, it was felt that using the terminology of the dominant framework in the field was appropriate. Thus, in the older adult group, the 8x8 decision space condition represented both an increase in complexity (in terms of decision space) and an increased in difficulty (in terms of an internal factor, amount of resources). This increase in difficulty is synonymous with a decline in resources, (or effort available): both represent an increased overall level of task demand.

Although decision complexity can not be separated from decision difficulty in any given decision, it is argued that this thesis is still able to highlight the issues of differences in decision source in determining task demand. For the majority of the experimental conditions in this thesis, the differences between decision complexity and decision difficulty, as the main variables manipulated to increase task demand, are explored, by accounting for task difficulty in using a within-participants design. In other words, a baseline level of task difficulty was established by keeping the decision makers and the decision environment consistent across conditions. This allowed an additional increase in task demand through decision difficulty, as defined by time pressure, to be measured against an increase in decision complexity.

The variety of responses in the information acquisition process to demand source is evidence that demand source may influence decision making more than has previously been recognised in the E-Af framework. It is suggested that E-Af should be modified to acknowledge these differences. Whether these differences are qualitative or quantitative in nature is yet to be determined.

10.7 The hierarchy of adaptivity

The over-arching aim of this research program was to explore the concept of hierarchy of adaptivity in the information processing underlying decision making. The studies reported in this thesis provide support for such a hierarchy. Three levels of cognitive resources were quasi-experimentally represented in this thesis: baseline, cognitively optimal populations in Chapters 2 and 3 and Chapters 6 and 7, a population with diminished cognitive resources in Chapters 4 and 5, and a population with enhanced resources in Chapters 8 and 9. Each of these populations was presented with conditions of increased task demand, via different demand sources. As such, each study represents a particular balance between task demand and computational availability; in other words, each study represents a different point along the effort axis of effort-accuracy continuum (see Figure 10.1). As outlined in Chapter 1, Section 1.4.2, Figure 10.1 is a representation of a decision maker's effort-accuracy continuum on different two decisions. The task demand of a decision is represented by the red and blue lines, and the maximum amount of effort available to, or resource limit of, the decision maker, is represented by the green horizontal line. This will be higher for a cognitively-enhanced population, and lower for a population with diminished resources. Even for each decision maker, this fixed resource limit will also vary across and within decisions, depending on competing demands on attention and working memory. As demand increases, and that those with more resources will adopt progressively more cognitively-economical strategies at a later point than a group with fewer resources. As such, in the face of equivalent task demand, a group with more cognitive resources will adopt less severe cognitive streamlining than a group with fewer resources.

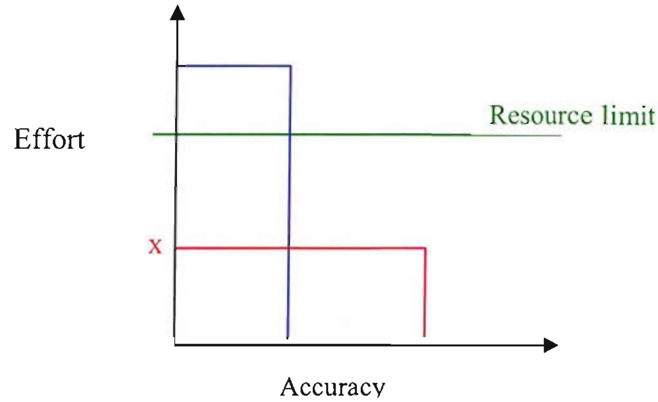

Figure 10.1 An illustration of the effort-accuracy continuum, with a low demand decision (X) and a high demand decision (Y)

The results reported here are, largely, consistent with these predictions. Within each of the three groups, in each case and regardless of demand source, participants adopted more cognitively-economical strategies as task demand increased (see Table 10.1). Between groups, each group adopted different degrees of cognitive economy in the face of equivalent task demand. When demand was increased by increasing decision complexity, the cognitively-optimal group demonstrated cognitive economy in terms of a relative decrease in the amount of information processed, particularly in terms of decision time and the number of acquisitions made. Younger adults took proportionally less time and made proportionally fewer acquisitions on the high complexity decision than would be predicted from the baseline, low complexity decision.

A cognitively-diminished population adopted more severe cognitive economy than the cognitively-optimal population. As well as spending proportionally less time and making proportionally fewer acquisitions as complexity increased, older adults became more attribute-led in their search pattern. Thus, it may be argued that diminished resources led to the adoption of more cognitively-economical, non-compensatory decision strategies in the face of a fixed level of task demand, when compared to a cognitively-optimal population.

In terms of enhanced resources, support for the E-Af is not as clear, but is not inconsistent with the theory. No clear differences were visible between the expert and novice groups in the face of increased decision complexity.

When task demand is operationalised as difficulty, the studies reported herein do provide some support the hierarchy of adaptivity. The cognitively-optimal population demonstrated evidence for cognitive economy in the face of increased difficulty, in terms of a reduction in the amount of processing. Younger adults took significantly less time to make their decisions, made fewer acquisitions, and accelerated their processing. The cognitively-diminished population demonstrated a greater degree of cognitive economy than the baseline population: in addition to reducing the amount of processing in terms of the decision time and number of acquisitions, they also demonstrated selectivity of processing across attributes. In other words, while some attributes were processed, others were ignored. Compared to medical students, the group of experts (i.e. those with enhanced resources) demonstrated a lesser degree of cognitive economy. While both medical populations demonstrated a reduction in amount of processing in terms of reduced decision time and more time on the subjectively most important attribute under conditions of greater task difficulty, the medical students made significantly faster acquisitions, while the medical experts did not. Thus, a progressively more cognitively-economical response to increased task difficulty can be seen across the three experimental groups: the group with enhanced resources demonstrating the least, and the group with diminished resource the most, degree of cognitive economy. Again, this hierarchy of response is consistent with the predictions of the E-Af (Payne *et al.*, 1993).

It is suggested that different results between the studies reported here, and other studies (Biggs *et al.*, 1985; Billings & Marcus, 1983; Klayman, 1985; Onken *et al.*, 1985; Payne, 1982; Payne *et al.*, 1988; Payne & Braunstein, 1978; Shields, 1980; Sundstrom, 1987), provide support for a hierarchy of adaptivity. It has been argued that these differences may be representative of different balances between task demands and resources across studies, and hence are representative of adaptivity in responding to changes in this balance.

10.8 Broad methodological criticisms

There are several methodological issues that may be of relevance to this thesis. First, as outlined in Chapter 2, examining group data does not enable conclusions about specific decision strategy usage to be drawn. It is recognised that the strategy of one individual may be effectively cancelled out by another, when information acquisition patterns are combined in a group. For example, one decision maker may be employing a non-compensatory strategy, such as the lexicographic strategy, while another decision maker may be employing a compensatory strategy such as weighted additive difference. When such data are aggregated, this different use of strategy would not be apparent. However, while identifying specifically which strategies are employed under different conditions is important, it would be premature to focus on individual strategy shifts. This thesis was concerned with broad changes in strategy usage in response to increases in task demands. Once these have been established, research can focus on specific strategies, in studying the information acquisition pattern of each person. Arguably, using group decision strategy data is a stringent test of the strength of the effects of increased task demand, and for the predictions of the E-Af (Payne *et al.*, 1993). Clearly, for effects to be visible, a high proportion of the group must be adopting a similar type of strategy. The fact that individual decision makers shift strategies in similar ways provides support for a model, such as the E-Af, which makes predictions about all decision makers.

Second, as mentioned in Chapter 2, it is possible that the traditional measures of information acquisition that have been used in the literature (TdTIME ACQ, TperACQ, PTMI, VARATT, VARALT, and PATTERN) do not adequately reflect the information acquisition process (see Chapter 2, Section 2.3). Although these variables are well-established, and commonly used, their usefulness should be examined further. Data from the Mouselab programme may be used to generate more measures (see Appendix B), which may assist in identifying decision strategies. For example, it may be useful to consider the degree of repetition (Mrep in Appendix B) in acquiring information from a decision space: more efficient non-compensatory strategies should involve accessing information fewer times than compensatory strategies. Both the traditional measures and new measures, which can be derived from the Mouselab programme, should be compared to determine the degree to which they relate to aspects of the information acquisition process. The degree of correlation between both new and old measures could be explored, and then a principal components analysis conducted to explore the dimensions covered by the measures. This process was felt to be beyond the scope of this thesis, but if future analysis of these new measures indicates that they cover dimensions that the old ones do not, it may be useful to examine them in future research

Another issue that must be discussed was the decision to use a MANOVA rather than ANOVA, or even *t*-tests, which have been adopted in past research. Employing an ANOVA for the seven dependent variables (DVs) examined in these studies (TdTIME, ACQ, TperACQ, PTMI, VARATT, VARALT, PATTERN) would have been unsuitable, due to the degree of correlation between the variables, which is evident in the correlation tables presented in each chapter. MANOVA is a generalisation of ANOVA to situations in which there are several related dependent variables; it involves testing whether mean differences between (or within) groups on a combination of DVs are likely to have occurred by chance (Tabachnick & Fidell, 1996). It does this by creating a new DV, a linear combination of the measured DVs, which maximises group differences. When there is more than one independent variable, as when groups are being compared in Chapters 4, 5, 6, 7, 8, and 9, the MANOVA creates a different linear combination of DVs for each main effect and interaction (Tabachnick & Fidell, 1996).

MANOVA is a robust technique which, as outlined in Tabachnick and Fidell (1996, p. 375-376), has advantages over an ANOVA approach. First, by measuring more than one DV, it improves the chance of finding exactly what changes as a result of different treatments and their interactions. Second, in comparison to a series of ANOVAs, MANOVA protects against the likelihood of a Type 1 error, which would otherwise result from multiple tests of correlated DVs. It is a more stringent and conservative test than ANOVA. Third, MANOVA has been demonstrated to be more sensitive than ANOVA, revealing differences not found in separate ANOVAs. Thus, due to the number and degree of correlation between DVs, it was felt that MANOVA was the best statistical approach to take in this thesis.

Arguably, it would have been possible to conduct two separate MANOVAs and one ANOVA for the 7 dependent variables, as these 7 are divided into 3 larger factors: 3 measures of the amount of information processed, 2 measures of selectivity of processing, and 1 measure of pattern of search. However, this idea was rejected for several reasons. First, the literature suggests, and as is evident in the correlation tables presented in each chapter, that there is a high degree of correlation between the dependent variables. Second, it was felt that a single MANOVA would be best in terms of parsimony. Third, it was felt that a single MANOVA would be more conservative, as the categorisation of the 7 variables into the three categories is imposed and not data driven (i.e. has not been supported by a principal components or factor analysis). Thus, although the most conservative approach, it was felt that a single MANOVA was best suited for analysis in these studies.

There is a negative aspect to employing such a conservative approach, but this was recognised and attempts were made to manage any difficulties. MANOVA assumes variables change in consistent ways in relation to each other. However, by comparing the different correlation tables across chapters, it is clear that correlations between variables vary; they do not correlate consistently. Thus, adopting such a conservative approach as the MANOVA may run the risk of making a Type 2 error. In addition, MANOVA is so stringent it sometimes fails to report interactions that may, in effect, cancel each other out (Tabachnick & Fidell, 1996). As occurred in Chapter 5, there were interactions that were not strong enough to be visible through the new linear DV but were there nonetheless. Specifically, the young and older adult groups differed in their response to VARATT and PTMI as a function of time pressure. Tabachnick & Fidell (1996, p. 401) recognise that an irritation of MANOVA is that a non-significant multivariate *F*, but a significant univariate *F* for one of the DVs may occur, as seen in Chapters 5, 7, and 9.

They point out that multivariate F is often not as powerful as a univariate F, and that in these instances the best approach is to report the non-significant multivariate F and outline the univariate F, as a finding of interest for future research. Thus, in accordance with this advice, significant interactions for individual DVs, which did not result in an overall interaction effect, were nonetheless reported, albeit in a conservative manner.

Another methodological issue relating to this thesis is connected with the tools used to collect data: specifically, the Mouselab program. A relevant criticism perhaps is with the ability of Mouselab as a program to report accurate process tracing. It is possible that the Mouselab methodology is not able to capture the speed of thought of the decision maker to truly reflect the information acquisition process (as the most sophisticated process-tracing device, an eye tracker, would), and in fact it may even alter the process. However, it has been argued that the Mouselab methodology comes very close to recording eye movements, in terms of speed and ease of acquisition, while minimising instrumentation costs and increasing ease of use for both participant and experimenter (Payne *et al.,* 1988). It has been pointed out that "an analysis of the time necessary to move the mouse between boxes in our display using Fitt's Law indicates that one could move between boxes in less than 100ms" (Card, Moran, Newell, 1983, p. 543). Payne *et al.* (1988) suggest that the time taken to acquire information in the Mouselab paradigm is limited by the time it takes the decision maker to decide where to move the mouse, rather than time delays incurred by the actual movement. This decision time-lag would also occur if an eye-tracker were being used. In addition, with reference to these studies in particular, it was felt that a computer-based process tracing process was favourable to an eye-tracker methodology with regard to the participant populations used. It was felt that older adults in particular might be uncomfortable with eye tracking equipment, while they all reported themselves to be computer-literate.

In response to the claim that the nature of the Mouselab program and the way in which the decisions are displayed may alter decision strategy selection, Payne *et al.* (1993) highlight the fact that the results of a good deal of research conducted without Mouselab have been replicated using Mouselab. In addition, to comments about the format of

Mouselab, Payne *et al.* (1988) reply that consumer information is often summarised in the form of tables in consumer magazines and these days, on websites, making this format ecologically valid.

10.9 Implications of this work and future research

As outlined in the beginning of this thesis, decision making is actually a very under-researched and poorly understood area of cognition, despite its importance to our everyday lives. This thesis outlines a structured research program into the information acquisition process underlying decision making, and how it is affected by changes in the balance between task demands and the cognitive resources of the decision maker. It is the first program which enables clear conclusions to be drawn about the predictions of the E-Af (Payne *et al.*, 1993), as critically the computational demand of the decisions (in terms of structure) are maintained, as are the populations of decision makers across types of demand source. Thus, it provides evidence for a hierarchy of adaptivity, which was previously only a theoretical implication of the E-Af. It is the first work to consider the effects of demand source and decision domain on the information acquisition process. In addition, it outlines the first studies examining older adults' and experts' decision making using an established process tracing system.

Clearly, this thesis is exploratory in the sense that it only provides a limited examination of the internal, external, and decision factors that influence the information acquisition process. It is also reductive, in that it does not explore the interaction effects of a range of these factors. However, this research provides the first structured approach to the examination of the effects of external, internal, and decision factors, which must be simplistic in the first instance. Arguably, this thesis outlines experimental evidence for previously largely theoretical ideas, such as the hierarchy of adaptivity, and provides a solid foundation for future research.

Future areas of research have been outlined both throughout the course of this thesis, and in this chapter. It is impossible to describe a comprehensive, suggested program of future research, as the possibilities are literally limitless. The field is a long way from defining predictive models of decision making, although this is clearly a desirable aim. First, a clear understanding of the effects of different internal, external, and decision factors on the information acquisition process must be reached: in particular internal and external factors are under-researched at this point. Specifically, the internal factors presented in this thesis (ageing and expertise) could be explored further, ideally in a move to process tracing in a natural environment. Ageing and expertise represent certain cognitive factors, but it is in the day to day functioning of older adults and experts that their cognitive abilities are manifested. Expertise may only truly influence cognitive functioning in an environment where it is acquired and implemented; similarly, ageing may bring compensatory benefits of experience that are not evident in a laboratory setting.

A general research program could follow this transition from lab to naturalistic environments, once the basic effects of different internal, external, and decision factors are determined. Such a shift necessitates changes in methodology and the means by which process tracing is achieved: portable eye tracking equipment, worn on participants' heads, may lead the way in this regard. Researchers should attempt progressively to combine different internal, external, and decision factors, and examine the effects of these combinations on the information acquisition process. For example, the internal factors outlined in Chapter 1, Section 1.7.2 have not been systematically studied in terms of information acquisition, and would provide a good starting point for this type of research. It is possible that the information acquisition process of older adults may not be affected by changes in their mood, while they may be with experts, as mood has been shown to affect decision outcome in this population (Dror, Charlton, & Péron, 2005). From this, judgements of the different computational values of these factors can be made, and these may enable more accurate calculation of a decision's overall cognitive cost. Judging the computational cost of a decision is part of the battle to make accurate predictions about decision making, and also helps determine which decision strategy would be the most effective.

Ideally, the aim of a future research program should be better to understand how to maximise decision efficiency and accuracy: if the cognitive cost of a decision and the cognitive resources of the decision maker can be estimated, then the ideal decision strategy can be consciously applied by the decision maker. Thus, ultimately, this research program may enable individuals both in a businesses or educational environment, and individuals on their own, to improve their decision making, rendering them more efficient, productive, and satisfied with their decision outcomes.

Appendix A

Table A1. Example decision set 1: 4x4 decision structure, with attributes I – IV, attribute values 1 -4, and alternative labels A-D

	I	**II**	**III**	**IV**
A	1	2	3	4
B	2	3	4	1
C	3	4	1	2
D	4	1	2	3

Table A2. Example decision set 2: 4x4 decision structure, with attributes V - VIII, attribute values 1 -4, and alternative labels E –H

	V	**VI**	**VII**	**VIII**
H	2	3	1	4
E	3	4	2	1
F	4	1	3	2
G	1	2	4	3

Table A3. Example decision set: 8x8 decision structure, with attributes I – VIII, attribute values 1 -4, and alternative labels A - G

	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
A	1	2	3	4	2	3	1	4
B	2	3	4	1	3	4	2	1
C	3	4	1	2	4	1	3	2
D	4	1	2	3	1	2	4	3
H	2	3	1	4	1	2	3	4
E	3	4	2	1	2	3	4	1
F	4	1	3	2	3	4	1	2
G	1	2	4	3	4	1	2	3

Appendix B

<u>Measures of information acquisition – existing* and proposed</u>

A) MEASURES OF TOTAL AMOUNT OF PROCESSING:

Rationale: Total amount of effort indicates if strategies are comp/non-comp, if any info has been ignored this also helps define search strategy.

Amount of information considered: (ACQ): Two measures – NACQ and PACQ

NACQ*(but called ACQ): ***Number of times info considered:*** *This is defined simply as the number of times cells considered (opened)*

PACQ: ***Proportion of info considered:*** *This is defined simply as the finite number cells (**NOT** repetitions) considered out of total number of pieces of info available.* ***Note*** *– each cell must only be counted once.*

4) **TdTime*:** ***Total time to decision***: *Time started on the matrix-time of decision – first MouseIn Time – last MouseIn Time*

BOXTIME: ***Total time spent in cells:*** Eliminates time spent moving between cells. Calculated by Σ MouseOut Time – MouseIn Time for all cells

TPERACQ*: ***Under Ms/cell, Average time per acquisition (NACQ) NOT INCLUDING MOVEMENT, i.e. BOXTIME average. Average on each visit not average of all cells. Average for count not for total number of possible cells.***

TPERCELL: ***Time per cell:*** *Some cells will have been viewed more than once, this is a measure of total viewing time for each cell including multiple viewings. You can view the breakdown of multiple viewings by moving the mouse on the relevant cell.*

B) SEQUENCE OF INFORMATION ACQUISITION (Pattern of processing)

Rationale: The priority placed gaining attribute-driven info or alternative-driven info can help define search strategies.

From info search protocols:

9) Sequence of information acquisition -> unitary measure of search behaviour SI (PATTERN*):

Is the search pattern attribute-based or alternative-based?

3 possible measures of sequence – a) interdimensional b) intradimensional c) interdimensional AND intradimensional. Payne et al. do not count c), dismiss them as transitions.

PATTERN* ***as defined by Payne et al.: number of search transitions within an alternative – the number of search transitions within an attribute / sum of the two numbers***

Answer between -1 (only attribute-based search) and 1(only alternative-based search)

10) Sequence of info acquisition MODIFIED (addition of combination strategies interdimensional + intradimensional) – Proportion of search strategies (PROPSS)

AttProp: ***Proportion of the overall search that is attribute-based***

AltProp: ***Proportion of the overall search that is alternative-based***

MixProp: ***Proportion of the overall search that is mixed (inter+intra dimensional)***

11) MREP: ***Measure of repetition:*** A single measure - how many times cells viewed. 1= good fit, cells viewed only viewed once. The further from 1 – measure of multiple viewings, possible indication of a) disorganized search b) working memory limitations (amount of cells with repetitions (NACQ)/total amount of cells without repetition)

C) SELECTIVITY OF PROCESSING

Rationale: Compensatory decision strategies e.g.(WADD, EQW, MCD) imply a CONSISTENT (i.e. LOW in variance) pattern of information acquisition, while non-compensatory (EBA, LEX, SAT) imply more a SELECTIVE (i.e. HIGH in variance) pattern of info acquisition.

PACQ: ***Proportion of info considered:*** *This is defined simply as the finite number cells (**NOT** repetitions) considered out of total number of pieces of info available. **Note** – each cell must only be counted once.*

PROPCELL: ***Proportion of time per cell:*** TPERCELL/BOXTIME

CPERCELL: ***Count per cell (number of times accessed) – can get an idea of this from the Msec page, from the colour coding of the time in each cell.***

NOTE: If the number is the cell is BLACK it means it has been looked at once, if the number is BLUE it has been looked at twice, and if it is RED it has been looked at 3 times or more.

PROPCOUNT: ***Proportion of counts per cell***

MEASURES FOR ATTRIBUTES

TIMEATT: ***Total amount of time (in ms) spent on each of the attributes***

TIMEATTPROP: ***Proportion of total time acquiring information that was spent in cells involving the most important attribute****: Most important attribute defined post-test. Get a measure for each attribute: amount of time spent in attribute/total time spent.*

COUNTATTPROP: ***Proportion of total counts (including repetions, NACQs) in any attribute***

SDTIMEATT (in ms): ***SD for the amount of time spent per attribute, across alternatives.***

SDPROPATT (VAR-ATTIB* in the literature)**:** ***SD for the proportion of time spent on each attribute***

SDCOUNTATT***: SD for the number of counts (NACQs) per attribute***

SDPROPATT_C: ***SD for the proportion of number of counts (NACQs) spent on each attribute***

MEASURES FOR ALTERNATIVES

TIMEALT: ***Total amount of time (in ms) spent on each of the alternatives***

TIMEALTPROP: ***Proportion of total time acquiring information that was spent in cells involving the most important alternative (final decision) (equivalent to PTMI***

COUNTALTPROP: ***Proportion of total counts (including repetions, NACQs) in any alternative***

SDTIMEALT (in ms): ***SD for the amount of time spent per alternative.***

SDPROPALT (equivalent to VAR-ALTER*): ***SD for the proportion of time spent on each alternative*** (less selective over alternatives for more attribute driven search)

SDCOUNTALT: ***SD for the number of counts (NACQs) per alternative.***

SDPROPALT_C: ***SD for the number of counts (NACQ) spent on each alternative***

Preference of search - Organization of the information search protocol

COUNTATT: ***Attribute Organization of info search protocol***: *number of times cells in each attribute looked at (whole column) (NACQS per attribute)*

COUNTALT: ***Alternative Organization of info search protocol***: *number of times cells in each alternative looked at (whole row) (NACQs per alternative)*

D) DECISION PERFORMANCE/ACCURACY OF CHOICE (not used in these studies)

FINAL: ***Final choice/decision.***

NOTE: Given in form: Alt X (Option Y) – Alt X will be the MASTER option, so if you have counterbalanced your data note this, not the label in the parathesis, which is linked to what the participant actually saw.

GAIN – Relative accuracy of choices, when alternatives not equivalent.

Appendix C

Description of hotel attributes (provided to participants, studies 1 -4)

Abbreviation of the attribute	Description of the attribute
Room Type	Includes things like size of room, size of bed, minibar availability, quality of furnishings, bathroom, and view.
Meal packages	Ranging from fully inclusive (drinks and snacks all day) to self-catering.
Restaurants	Relates to the number of restaurants and variety of food available.
Hotel Services	These include services such as room service, laundry, babysitting, etc.
Facilities	Includes things like a gym, tennis courts, a swimming pool, a 24 hour lounge bar, business meeting rooms, etc.
Comp. Extras	Includes things like toiletries, pressing of suits, use of facilities and sports facilities, guided tours, cocktail parties, and entertainment.
Trans. Time	Relates to time to get to and from the nearest airport: ranges from very close to very far.
Dis. Nr. Town	Relates to time to get to and from the nearest town: ranges from very close to very far.

Description of medical attributes (provided to participants, studies 5 -8)

Abbreviation of the attribute	Description of the attribute
Pulse	The patient's pulse rate measured in beats per minute.
BP	Blood pressure measured in millimeters of mercury (mm Hg).
pO2	Partial pressure of oxygen in the patient's blood. Measured in kilopascals (kPa).
Hist/ Descrip	Patient's recent medical history or a description of their presenting complaint.
GCS	Glasgow Coma Scale. A measure of the patient's conscious level, rated out of a maximum of 15.
Resp. Rate	Respiratory rate or number of breaths taken per minute.
Breath Sounds	An estimation of the patency of the patient's airway. Rated as normal, noisy, or stridor.
CV exam	The findings of a cardiovascular examination of the patient.

Appendix D: Pilot study

Introduction

The aim of this pilot study was to provide empirical validation for the categorization of the 8 attributes into two groups of 4: low and high subjective importance. The group of 4 high subjective importance attributes would be used in the reduced (4x4) decision matrices relating to hotels in studies 1 – 4 of this thesis.

Note that the 8 medical variables used in studies 5 – 9 of this thesis were ranked in terms of importance by the medical expert, on the basis of primary symptoms (i.e. factors that medical students are trained to ask first).

Method

Participants: 20 volunteers (8 males, 12 females, *M* 38, *SD* 7.2) from the Department of Psychology, University of Southampton, participated in this pilot study.

Stimuli/Procedure: Participants were presented with a list of 8 attributes relating to hotels (including their definitions/common examples), and asked to rank them from 1 -8, with no joint placements, in terms of their subjective importance.

Results

The data provided by this study was ordinal data, relating to the ranking of 8 attributes by frequency of selection.

Table 1: Frequency of ranking selections by attributes

	Attributes (frequency)							
Rank	**Room Type**	**Meal Packages**	**Restaurants**	**Hotel Services**	**Facilities**	**Comp. extras**	**Trans. time**	**Dist. town**
1	5	4	4	4	1	1	0	1
2	6	5	4	2	1	1	1	0
3	3	4	2	4	2	1	2	1
4	4	2	4	3	2	1	1	3
5	1	3	4	2	6	2	0	3
6	0	1	1	2	1	3	7	4
7	1	0	1	1	2	6	3	4
8	0	1	0	0	5	5	5	3

The cumulative percentage of the frequencies of selection for the top 4 rankings positions were examined, and the 4 attributes with the greatest cumulative percentages rankings 1 - 4 were identified (see Table 2) and selected for use in the reduced (4x4) decision matrices.

Table 2: Cumulative percentage values for rankings 1-4

Attribute	**Cumulative percentage on rankings 1-4**
Room Type	***90***
Meal Packages	***75***
Restaurants	***70***
Hotel Services	***70***
Facilities	30
Comp. extras	20
Trans. time	20
Dist. town	25

Discussion

The four attributes with the highest cumulative percentage on the top rankings (1-4) were selected. They were: room type, meal packages, restaurants, and hotel services.

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